PRODUCTIVE CAPACITY, CONTEXT, AND PERFORMANCE: THE MODERATING ROLE OF CONTEXTUAL COMPLEXITY

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PRODUCTIVE CAPACITY, CONTEXT, AND PERFORMANCE: THE MODERATING ROLE OF CONTEXTUAL COMPLEXITY

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This study sought to investigate the role of productive capacity in driving collective performance and, in so doing, provided initial empirical validation of Hausknecht and Holwerda's (2013) capacity-based perspective. Capacity emerged as generally predictive of performance, signaling, at least for now, its worthiness as a construct and the value of its associated measure. Additionally, the conceptual space of capacity was developed, with the construct positioned as a collective resource subject to contextual effects. While the evidence supporting contextual effects was meager, it was also promising as, under the right analytical conditions, an interaction between capacity and context emerged to predict performance.

BIOGRAPHICAL SKETCH

Jacob Alexander Holwerda was born in Sakskatoon, Saskatchewan, Canada on December 30, 1983. He attained his B.S. (Honors) in Industrial and Labor Relations in 2006 and his M.S. in Human Resource Studies in 2009 from the ILR School at Cornell University.

For Newman and Sally Holwerda

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CHAPTER 1

INTRODUCTION AND CONCEPTUAL BACKGROUND

For quite some time, organizational scholars have investigated the respective roles that human and social capital play within organizations as well as the economy at large (Becker, 1962; Schultz, 1961; Bourdieu, 1986; Coleman, 1988; Nahapiet & Ghoshal, 1998; Leana & Van Buren, 1999; Adler & Kwon, 2002). While work surrounding these intangible assets has largely emerged in separate literatures, more recent discussion of these concepts reveals a growing trend toward consideration of their interrelatedness (Burt, 2005; Nahapiet, 2012) and suggests that, within organizations, "social and human capitals become more entangled the more closely we look at them" (Spender, 2009: 10).

At the confluence of human and social capitals, then, lies the concept of organizational capital, a collective resource which simultaneously considers both individually-held human capital elements and the social and/or structural factors that enable them to be effectively leveraged and directed toward productive use. Working from the perspective that such collective resources are the most proximal drivers of collective performance (Ployhart, Van Iddekinge, & MacKenzie, 2011), the current work explores the nature and effects of organizational capital through the lens of productive capacity, a recently developed construct that reflects the collective proficiencies of a work unit's membership (Hausknecht & Holwerda, 2013).

While discussion of organizational capital, as a construct, is relatively recent, it shares substantial common ground with better-established concepts such as transactive memory systems, shared mental models, and group experience/familiarity that, at their most fundamental, rely on social conduits to effectively integrate and direct human capital elements toward collective performance. However, and despite these conceptual similarities, measurement of organizational capital and direct empirical modeling of its performance effects in context remain challenges. The current work aims to address these challenges, first, by placing productive capacity, a form of organizational capital, within the extant literature on collective resources and further developing it as a construct and operationalization of organizational capital. The dynamic framework inherent in the capacity-based perspective is invoked to describe the changing nature of organizational capital over time and how and why such changes connect theoretically to collective performance. Beyond this, theory surrounding potential moderators—namely contextual complexity—of capacity-performance relationships is developed. Theory and simulations suggest that productive capacity should be a strong predictor of unit-level performance and that the magnitude of capacity-performance relationships should increase under conditions of greater complexity. Utilizing a fine-grained operationalization of organizational capital, these hypotheses are tested using data collected from 400 units of a large U.S.-based service organization.

Productive Capacity as a Construct

Hausknecht and Holwerda (2013) propose a capacity-based perspective that examines drivers of collective function "in terms of the proportion of human and social capital utilization achieved by a given collective in a given period" (8). This perspective is based on the idea that any given collective possesses a theoretically determined and sustainable maximum functionality (Corrado & Mattey, 1997; Steiner, 1972) that is affected by the time-dependent accumulation of firm-specific human and social capital stocks by remaining/stable collective members, the addition of new members, and the depletion of such stocks by members who exit. More specifically, capacity is driven by: (i) extant member proficiencies (the general and firm-specific human capital and firm-specific social capital of collective members developed over time); (ii) newcomer proficiencies (the general human capital with which new members enter a collective); and (iii) departing member proficiencies (human capital stocks that members take with them in the event that they leave the collective as well as any damage such departures may inflict upon the collective social capital stock).[1] These properties combine to dictate the collective's stock of human and social capital that contributes to its effective and efficient function.

Following this, productive capacity encapsulates two related, but distinct, elements. First, it captures the dynamics of the collective human/social capital stock that occur over time—for instance, the accumulation of collective-specific experience or tenure—both in the absence and presence of member inflows and outflows. Second, it considers the alterations imposed on collective resources by human capital inflows and outflows as well as potential disruption to (Dess & Shaw, 2001; Shaw, Duffy, Lockhart, & Johnson, 2005; Summers, Humphrey, & Ferris, 2012) to collectively-held social capital.[2] Given these characteristics, productive capacity is defined here as *a form of embedded organizational capital that emerges continually and dynamically from: (i) individually-held stocks of general and firm-specific human capital; (ii) collective inflows and outflows of general and firm-specific human capital; and (iii) accumulation of and disruptions to firm-specific social capital* (Hausknecht & Holwerda, 2013; Spender, 2009; Bowman & Swart, 2007).

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[1] The capacity-based perspective also considers two other properties—positional distribution and time dispersion—which describe the potential (dys)functional effects that may arise from departure clustering (Hausknecht & Holwerda, 2013). However, as the immediate discussion focuses on human and social capital stocks that remain within collectives and positional distribution and time dispersion apply *only* in the case of member exit, discussion of those properties is left until later in the paper.

[2] Note that here and in the following discussion, social capital is considered as a public good that may be utilized to the success of the collective in which it is imbued (Nahapiet & Ghoshal, 1998; Spender, 2009) as opposed to a private good by which structural holes may be leveraged for individual success (e.g., Granovetter, 1973; Burt, 1997).

Productive Capacity and Collective Capital Stocks

Given the complexity and interconnectedness of these components, productive capacity represents a form of "embedded capital" which, itself, "exists as a gestalt; a complex agglomeration of human and separable capital that resists separation into the constituent parts that combine to produce it" (Bowman & Swart, 2007: 495). This resistance to separation blurs the border between human and social capital and, more broadly, the point where individually-held (human-capital-based) and collectively-held (social-capital-based) proficiencies meet (Bowman & Swart, 2007; Spender, 2009; Nyberg, Moliterno, Hale, & Lepak, 2014). The links between these forms of capital have long been recognized as has their interrelatedness (Coleman, 1988; Burt, 2005; Nahapiet, 2012; Schultz, 1962; Bowman & Swart, 2007).

For instance, social and human capital may act as complements. Specifically, social capital may enable the further development of human capital within collectives (Ployhart & Moliterno, 2011) by facilitating effective socialization processes as well as the transfer of tacit knowledge to newcomers, essentially driving the co-evolution of both capital forms. Further, recent treatments of these capital forms have demonstrated a trend to toward their simultaneous consideration, if not their combination (Nahapiet, 2012; Spender, 2009). Indeed, the coexistence and interaction of these two forms of capital—and the ambiguity that such interactions generate—may represent a critical source of their respective values to firms as they may (i) serve as drivers of competitive advantage due to ambiguity surrounding their functional mechanisms (Bowman & Swart, 2007: 490), (ii) enable organizations to employ superior production processes (Lewin, 2005), and (iii) may become more sophisticated and valuable with increased use (Kraiijenbrink, Spender, & Groen, 2010).

The blurring of human and social capitals as components of productive capacity maps well onto Spender's (2009: 7) conception of organizational capital—"the sum of the organization's human and structural capital." While a significant proportion of structural capital—"resources developed to help the firm integrate its factors of production and division of labor, and ensure the employees' skilled activities are well aligned to its objectives" (ibid.)—may be codified and tangible, critical to the current discussion, a relational component, defined by its informality and embeddedness within the organization or collective, exists as well:

> Such relational assets seem to be 'of the organization'; persisting beyond any particular employee's tenure, and standing apart from them and their skills, and so differentiable from the individualistic or personal dimensions of 'human capital'(7).

This relational component, held across collective members and external to (but derived from) individual employees, is a key aspect of productive capacity and represents a form of capital as it adds economic value to future organizational operations (Lewin & Baetjer, 2011).

Taken together, these characteristics underscore critical assumptions of the capacity-based approach. First, organizational capital is *emergent*. Specifically, the blurring of human and social capital to form collective-level resources suggests largely irreducible interactions underlie its formation. Thus, although composed of individual-level human and social capital components, the "fuzzy" (i.e., complex and non-additive) composition (Bliese, 2000) of such resources implies that they are only partially isomorphic with their individual-level counterparts. Second, organizational capital is *relational* in nature—at least some mechanisms supporting collective function will be held collectively (Spender, 2009; Summers et al., 2012), that is across individuals, assuming any interdependence among collective members. Thus, under the capacity approach, social capital plays a direct role as an enabler of collective knowledge sharing and transfer of information that makes possible the processes and patterns that facilitate alignment and integration of employee efforts.

A third assumption is that organizational capital is *temporally contingent.* This assumption derives from the view that competitive advantage is achieved at the level of the collective or firm and is the result of heterogeneous resource distribution across such units of analysis and thus, primarily reliant on the development of firm-specific capabilities (e.g., organizational capital) that enable superior organizational services and processes (Penrose, 1959; Barney, 1991). Given the firm-specificity of these resources, they cannot be easily acquired outside of the firm, but rather must generated from within. Due to the necessity of "in-house" development, it follows that these resources take time to develop and are likely subject to path dependence and ambiguity in their emergence, qualities that further suggest their value in driving competitive advantage.

With this in mind, the capacity-based perspective adopts a focus on temporal elements with respect to resource development and degradation. While resource degradation is viewed as stemming primarily from member departures over time, collective resource accumulation is assumed to rely on the within-collective, tenure-based accretion (and eventual complex combination) of individuals' respective proficiencies, or competencies in meeting firm-specific role demands (Lance, Kavanagh, & Brink, 2002). Notably, proficiency is not synonymous with tenure, but rather is assumed to approach an asymptotic maximum where "additional time does little to increase proficiency" (Hausknecht & Holwerda, 2013: 218). Finally, alongside the firm-specific components of both human and social capital, the capacity-based perspective acknowledges the role played by general human capital in generating collective-level productive resources, specifically via its function as a foundation upon which organizational capital can be constructed.

Work surrounding several collective-level constructs related to the performance and function of collectives lends support to the idea that (i) important functional resources, although derived from individuals, exist as emergent relational assets "of the collective" and (ii) to some degree, require time to develop. For instance, Huber and Lewis (2010: 7) put forth the concept of cross-understanding—"the extent to which group members have an accurate understanding of one another's mental models." These authors emphasize both collective and relational aspects of team function, focusing on members "understanding what others know, believe, are sensitive to, and prefer" (9) and further, suggest that the nature of cross-understanding is temporally dependent (cf. 16). Related constructs, although differentiated from cross-understanding along content lines, are similarly subject to temporal dependence and relational in nature.

For instance, transactive memory—"the shared division of cognitive labor with respect to encoding, storage, retrieval, and communication of information from different knowledge domains, which often develops in close relationships" (Brandon & Hollingshead, 2004: 633)—possesses an implied temporal as well as a relational element. Further, the construct is positioned as "an evolving rather than a static phenomenon" (633) that is subject to "refinement over time" (640) as collective members grow familiar with within-collective distributions of expertise. In the same vein, shared mental models—"organized understanding of relevant knowledge that is shared by team members" (Mohammed & Dumville, 2002: 89)— also represent collective relational assets. While, a significant amount of work on shared mental models has focused on how to train teams to possess them (Ilgen, Hollenbeck, Johnson, & Jundt, 2005), their development is still subject to time-dependent factors such as learning processes and exchanges with other collective members over time (Huber & Lewis, 2010).

Other work also indicates the relational nature and temporal contingence of collective resources. For instance, Littlepage, Robison, and Reddington (1997) discuss the role of group experience—"experience working with other group members" (133)—in promoting positive team performance via the development of group-relevant cognitive structures. These authors further suggest "that a modest degree of time (and interaction) may be needed to allow for recognition of expertise" and that "social processes…promote recognition of member expertise" (145). Closely related, Reagans, Argote, and Brooks (2005) connect experience working together—"the cumulative production history of pairs of individuals" (870)—to positive team functioning through enhanced coordination and information-sharing abilities. More specifically, these authors suggest the time-dependent importance of developing "relationship-specific heuristics that enhance how well people performing distinct roles interact with each other" (872). Beyond this, Harrison and colleagues (2003) connect member familiarity—"interpersonal experience with one another on a variety of activities and over a lengthy time frame" (639)—to improved team performance. Finally, team learning, defined as "relatively permanent changes in the knowledge of an independent set of individuals associated with experience" (Kozlowski & Bell, 2003: 349), once more indicates the relational and temporal elements that may drive collective function.

From a conceptual standpoint, the construct of productive capacity also shares common ground with Ployhart & Moliterno's (2011) conception of the unit-level human capital resource (HCR)—"a unit-level resource that is created from the emergence of individuals' knowledge, skills, abilities and other characteristics (KSAOs)" (128). However, subtle but important differences between capacity and the HCR exist surrounding what comprises a capital stock—for instance, the proposed role of social capital. Under the HCR model, social capital is conceived of as generating "emergence enabling states" (Ployhart & Moliterno, 2011: 137) that provide the backdrop upon or conduit by which HCR emergence occurs. Incorporating this conception, the capacity-based approach recognizes the enabling role of social capital in collective-level human capital development—i.e., its complementarity with human capital (Nahapiet, 2012; Coleman, 1988)—but, in some contrast, makes more explicit consideration of firm-specific social capital elements utilized by the collective and views social capital as a key and direct driver of collective proficiency. Thus, the aim here is to build upon the conception of unit-level human capital by integrating its counterpart, collective social capital.

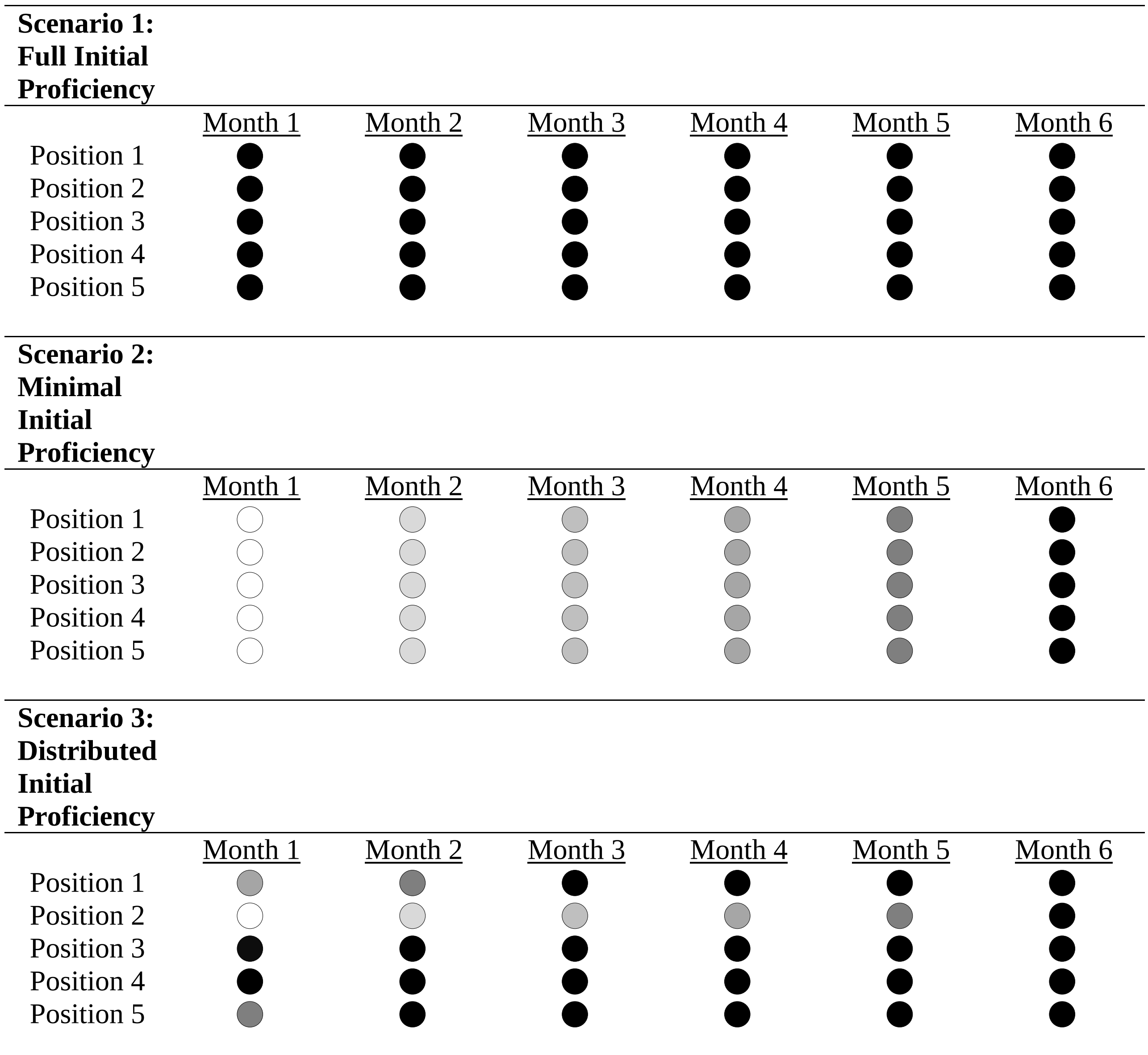
Another key difference in these perspectives surrounds the conception of stocks of capital. The HCR model acknowledges that "the human capital resource is constructed and reconstructed via the repeated aggregation (e.g., staffing and turnover cycles) of employees with relatively fixed levels of cognitive ability" (135) and that the HCR may be modified via "knowledge acquisition and assimilation" (143) in accordance with the concept of absorptive capacity (Zahra & George, 2002). However, the capacity-based perspective extends this idea by recognizing that such construction and reconstruction can occur outside of the innovative and strategic context (ibid.) implied by absorptive capacity (e.g., an operational context) as well as in the absence of either or both member hiring or departure—i.e., through the tenure-based accumulation of firm-specific knowledge and skills in the forms of both human and social capital. Thus, while the HCR approach considers stocks as defined at a given point in time (Ployhart et al., 2009; Ployhart, et al., 2011), the capacity-based approach works from the perspective that "stocks" exist only as momentary observations of dynamic resources that are, for better or worse, constantly evolving. More simply, stocks themselves exist as dynamic, longitudinal entities. Any perceived stasis of such stocks represents only a "snapshot" of a continually developing resource. Thus, the capacity-based perspective works from the idea that collective capital stocks are fundamentally longitudinal in nature despite their common definition as stable entities.

Figure 1 illustrates both moment-specific "stocks" of capital and the changes to those stocks that occur as a result of refinement, group learning, and repeated member interactions over time (darker circles indicate higher proficiency levels). Importantly, none of these changes are the result of member inflows or outflows with respect to the given collective. Three potential scenarios by which proficiency accumulation can occur are shown. Across all three scenarios, the momentary (in this case, monthly) "stock" of collective capital is depicted by each monthly column. The "month" labels are used here for ease of discussion and presentation (although they represent the most common time interval to be of use to organizations in practice).[3]

The first scenario illustrates a situation in which all members of a collective have full or maximum proficiency at the beginning of the observation period. Under these conditions in which all members of the collective have reached their respective asymptotic maximum proficiency (note that this includes both firm-specific elements of human capital as well as social capital), the capacity of the collective is stable over time (barring member inflows and outflows). Significantly, this situation represents the *only* circumstance under which collective capital stocks will remain stable across time. By comparison, in the second scenario, each member of the collective is minimally proficient at the start of the observation period. In this case, assuming that proficiency is accumulated in a regular fashion over time and that it takes six months for

[3] Under the capacity-based approach, although the intervals that define time dimensions are fixed—i.e., constant in length—the length itself, at least in theory, is infinitely variable (e.g., seconds, hours, quarters, years, etc.).

FIGURE 1
Proficiency Configurations for Productive Capacity under Zero-turnover Conditions



each member to both acquire the firm-specific human capital necessary for task performance and the firm-specific social capital necessary for collective performance, the "stock" of collective capital varies on a monthly-basis and grows over time. Finally, the third scenario illustrates a more realistic situation in which proficiency is distributed in different amounts across collective members. For those that are already maximally proficient, their individual proficiency remains constant; for those whose proficiency is less than maximal, it accumulates as before. Taken together, these scenarios demonstrate how collective capital stocks may be generated, improved, and maintained even in the absence of member inflows and outflows.

Together, the three scenarios are indicative of the importance of a longitudinal and dynamic conception of collective capital "stocks". In particular, one would expect that the collective depicted in Scenario 1 would be the best off of the three as it contains fully proficient members for the entire observation period. In terms of collective function, it would be followed by the collective depicted in Scenario 3 and, finally, the collective in Scenario 2 would be the least well off given that it has the lowest proportion of dark circles across the observation period. Despite varying dynamic effects, each scenario has reached full proficiency in Month 6 of the observation period. Thus, examining only the collective capital stocks—i.e., momentary snapshots—ignores important dynamic elements underlying its formation and further, if that snapshot is taken in Month 6, the three different collectives would appear identical.

Collective Capital Flows

The second element captured by capacity surrounds the potential impacts of capital flows—"employee movement in and out of units" (Reilly, Nyberg, Maltarich, & Weller, in press: 1)—as well as potential disruption to social capital caused by such movement. Flows of collective capital, particularly those representing outflows via turnover, are critical to determining a given collective's ability to function efficiently and effectively. Both longstanding and more recent work has emphasized the importance of capital flows in determining collective function. Though this stream of literature has generally focused on human capital, the potential for capital flows to generate effects on social capital as well has not gone unnoticed (e.g., Leana & Van Buren, 1999; Hausknecht & Holwerda, 2013; Reilly et al., in press). Among the first to address the importance of such flows for collective function, Dierickx and Cool's (1989) "bathtub metaphor" aimed to describe their role with respect to the accumulation of productive stocks of capital (research and development capabilities, in particular) at the organizational level over time:

> …at any moment in time, the stock of water is indicated by the level of water in the tub; it is the cumulative result of flows of water into the tub (through the tap) and out of it (through a leak). In the example of R&D, the amount of water in the tub represents the stock of know-how at a particular moment in time, whereas current R&D spending is represented by the water flowing through the tap; the fact that know-how depreciates over time is represented by the flow of water leaking through the hole in the tub (1506).

While it is clear from the metaphor that these authors had the formation and degradation of strategic assets in mind, their logic applies equally well to the flow of employees into and out of collectives, particularly with respect to the dynamism in resources implied by employee movements (Ployhart et al., 2009).

More recent work has aimed to explicitly delineate and quantify what such flows entail for collective function. Hausknecht & Holwerda (2013), for instance, described five properties that explain the emergent impacts of flows of collective capital on collective function. Three of these properties—extant member proficiencies, leaver proficiencies, and newcomer proficiencies—deal explicitly with the level of human and social capital possessed by collective members over time. The remaining two properties more directly concern the patterns of interrelationships that may emerge between multiple outflows within a collective, affect its productive capacity, and, ultimately, its performance.

The first, *positional distribution*, refers to the extent to which departures occur across multiple positions within a collective as opposed to being constrained to a single position. The second, *time dispersion*, considers the extent to which departures among multiple members of a collective are temporally proximal to one another. Positional distribution generates effects on collective function because, to the extent that human capital flows (outflows via turnover and inflows via replacement) are constrained to one or a few positions, a stable core of collective members remains intact as does the collective's productive capacity. Time dispersion of outflows affects collective performance since higher dispersion of departures across a time period (as opposed to multiple outflows occurring simultaneously) implies that a larger proportion of the collective remains intact at any given time to abet potential losses to collective function (ibid.). Taken together, these last two properties capture more explicitly the degradation of collective resources suggested by Dierickx and Cool (1989) by modeling the outflows of human capital associated with individual departures that affect collective human capital levels as well as potential disruption to collective social capital.

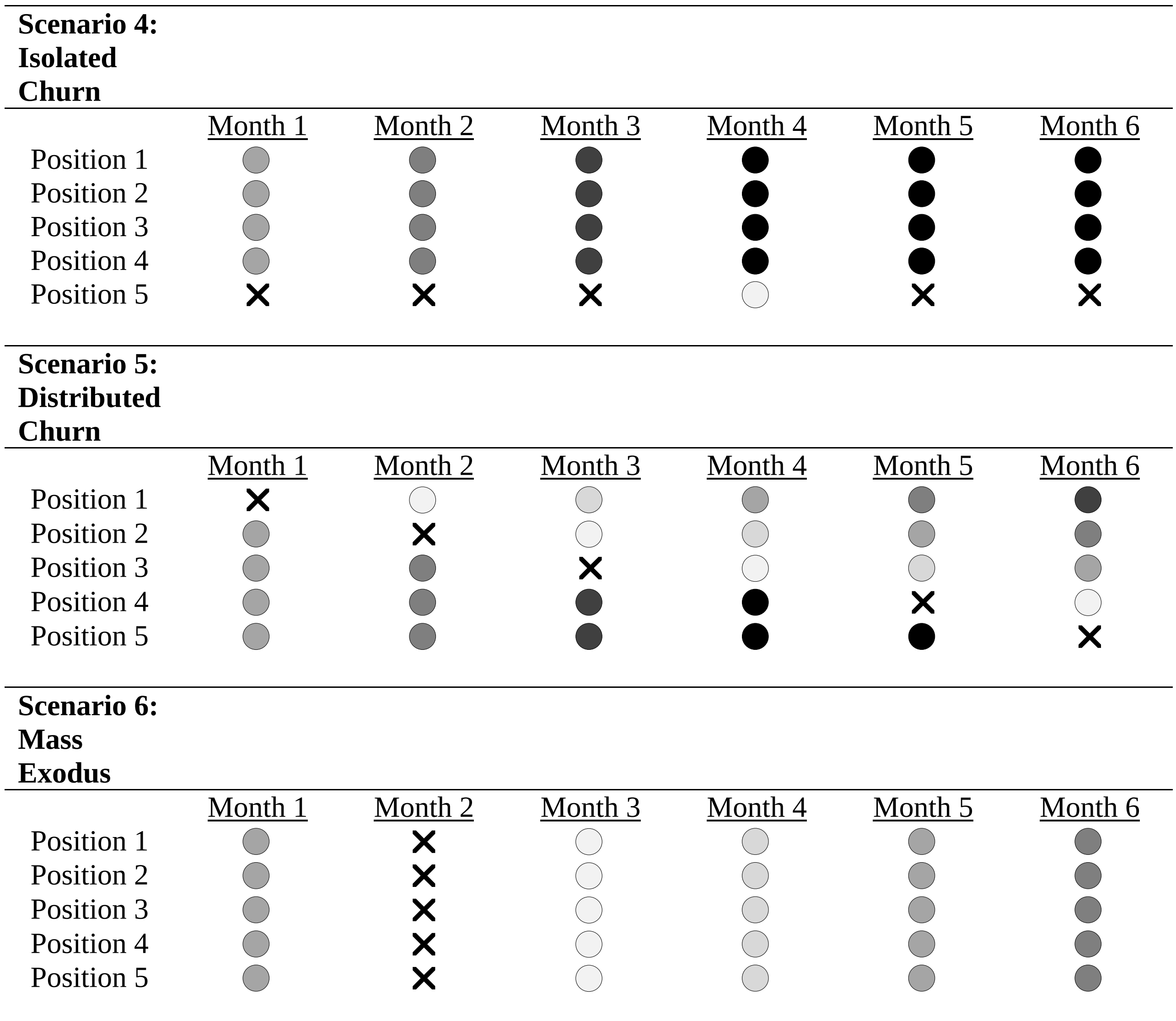
While productive capacity may be affected by human capital outflows and social capital disruption, the capital stocks associated with extant members and inflows associated with newcomers may, in many cases, be as or more important in determining potential collective function (Hausknecht & Holwerda, 2013; Nyberg & Ployhart, 2013). Thus, while outflows may disrupt or detract from a given collective's ability to function at maximum levels, the productive capacity of the collective is not solely contingent upon member movement. Rather, productive capacity is itself indicative of a collective's ability to "coalesce into a coordinated, more efficient whole" (Hausknecht & Holwerda, 2013: 218) with higher levels of capacity suggesting greater ability to maintain and leverage interpersonal relationships and function according to established group norms. More simply, while outflows affect capacity, capacity is neither synonymous with nor fully determined by outflows or turnover (Hausknecht & Holwerda, 2013).

While productive capacity, as a construct, is newly developed, it does share common ground with several other constructs that address collective capital flows and their predicted effects on collective function. For instance, Summers, Humphrey, and Ferris (2012) discuss team member change and how the phenomenon generates disruption or flux within collectives. Specifically, "flux describes the time after change occurs and before a team has restructured" or "an unstable, unbalanced, or changing pattern of interaction in a collective" (315). In common with the capacity-based perspective, these authors point out the collectively-held component of what remains despite capital outflows in the form of employee departures noting that, "[w]hen member change occurs, some of a team's coordination patterns remain because linkages and routines exist among remaining members" (320). It is precisely these routines and linkages that are affected by flows of capital and captured by "extant member proficiencies" in the capacity-based perspective.

Also related to member flows and productive capacity are collective constructs such as tenure heterogeneity ("heterogeneity within a work unit with respect to organizational tenure"; Heavey, Hausknecht, & Holwerda, 2013: 437), average tenure, and newcomer concentration ("the extent to which very recent hires…comprise the work unit"; Hausknecht, Trevor, & Howard, 2009: 1069). Each of these constructs acts as a proxy for the effects of flows on collective composition as well as considers the potential disruptive effects of capital flows on collective function. Finally, Nyberg and Ployhart (2013) offer "context-emergent turnover" (CET) theory as a means to describe how unit-level function may be affected by the accumulation of individual-level employee flows. Like the capacity-based perspective, CET theory views collective turnover as an emergent phenomenon but differs in its focus on individual KSAOs as opposed to collective-specific capabilities. More specifically, while CET theory frames collective outflows as the quality and quantity of aggregated losses of KSAOs, the capacity-based approach focuses on the impact of flows on firm-specific components of collective function which have been found to be more proximal indicators of collective performance (Ployhart, Van Iddekinge, & MacKenzie, 2011).

As before, the effects of capital flows on collective function are temporally contingent. *Figure 2* (adapted from Hausknecht & Holwerda, 2013: 219) illustrates this phenomenon in action. Depicted in the figure are three ideal-type scenarios in which the same number of absolute departures occurs within a given collective. In Scenario 4, departures are constrained to a single position (position-restricted) but are spread over multiple time periods (time-dispersed). In Scenario 5, departures are spread across multiple positions (position-distributed) and multiple time periods (time-dispersed). In Scenario 6, departures are once more spread across multiple positions (position-distributed) but occur in the same time period (time-restricted). Conceivably, one might expect the collective depicted in Scenario 3 to suffer the most detrimental effects of member departure as, in Month 2, all members depart and thus leave no experienced employees within the collective to drive performance or abet losses. The collective in Scenario 5 should also

FIGURE 2
Proficiency Configurations for Capacity Under 100% Turnover Conditions



suffer significant detrimental effects as relatively experienced collective members depart repeatedly, suggesting relatively greater process losses and performance deficits than would be apparent in Scenario 4 where a stable core of employees remains intact throughout the observation period.

Temporal effects are once more key to the understanding of collective function. Specifically, the “snapshot” inherent to a purely stock-based conception—as might be observed in a single monthly column—belies the fact that the effect of flows on collective function changes over time. While the collective depicted in Scenario 4 develops relatively high proficiency over time due the presence of a stable contingent of employees, the eventual combined effects of capital flows and tenure-based proficiency accumulation are less intuitive in the remaining scenarios. Specifically, the collective in Scenario 6 (mass exodus) suffers large losses following the *en masse* departure of members in Month 2 while the collective depicted in Scenario 5 is better able to buffer losses as they occur as indicated by the larger proportion of darker circles in most monthly columns. Nonetheless, and despite the damage suffered via a large human capital outflow, the collective in Scenario 6 recovers relatively well, and as will be shown later, actually functions at a higher level than that in Scenario 5 by the end of the observation period.

Operationalizing Capacity

To capture the array of effects suggested by the interplay of the aforementioned properties, the capacity index re-conceives individual human and social capital accumulations and turnover events on a lattice, or grid, of binary outcomes (in its simplest form). The lattice, as a whole, is representative of the organizational capital present in the collective. This conception is based on the Ising model, common to the field of statistical mechanics (e.g., see Sethna, 2006). Such models were originally designed to describe the spins of atoms within metals under the influence of magnetic fields that encouraged individual atoms to either align or dis-align with one another. While somewhat distant in its foundations from the current work, the capacity index, originally designed to model turnover events, applies the mathematics and logic inherent to these models to human capital flows/accumulations and social capital disruptions/ accumulations within collectives—i.e., groups, teams, work units, branches, and so on. The key difference, however, lies in the fact that instead of atomic spins arranged according to two spatial dimensions, *x* and *y*, the capacity index considers human and social capital accumulations and turnover events arranged according to two other dimensions, time, *t*, and positions, *p*.[4]

When considered in this fashion, the mathematical formalism and logic surrounding Ising models can be brought to bear on inquiries regarding the nature of human and social capital within collectives and how they are affected by individual departures and proficiency accumulations. Specifically, Ising-based investigations commonly use a measure of "magnetization" to describe the end state of a given system. In the same vein, the capacity index (Hausknecht & Holwerda, 2013) describes the functional end state of a given collective within a given time period by applying this measure with an additional factor, *N*, that scales the measure for group size and facilitates comparability among different groups (as well as groups of changing size). Specifically, the capacity index is calculated as:

$$\text{Capacity Index} = (\textstyle\sum_i s_i)/N$$

where s_i denotes the value of a given site in the lattice determined by the proficiency accumulation of a given member to that period and the summation term, $\sum_i s_i$, captures the

[4] For the current discussion, I follow Hausknecht and Holwerda (2013) in treating "positions" as generic and interchangeable although differences in employee contribution via status as core or peripheral (Humphrey et al. 2009) are acknowledged.

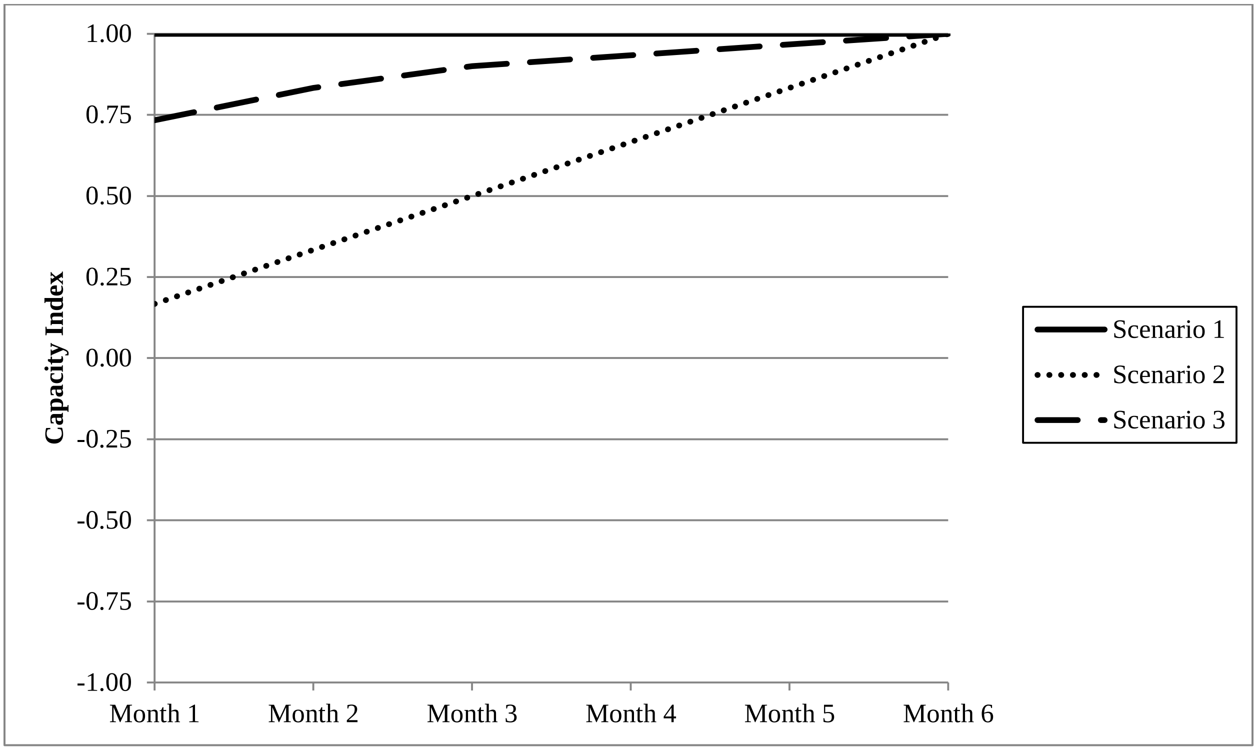
FIGURE 3
Capacity Calculations for Zero-Turnover Conditions

Scenario 1: Full Initial Proficiency						
	Time					
	Month 1	*Month 2*	*Month 3*	*Month 4*	*Month 5*	*Month 6*
Position 1 (p_1)	1	1	1	1	1	1
Position 2 (p_2)	1	1	1	1	1	1
Position 3 (p_3)	1	1	1	1	1	1
Position 4 (p_4)	1	1	1	1	1	1
Position 5 (p_5)	1	1	1	1	1	1
$\Sigma s_{i,m}$:	5.00	5.00	5.00	5.00	5.00	5.00
$\Sigma s_{i,m}/N_m$:	1.00	1.00	1.00	1.00	1.00	1.00
$\boldsymbol{\Sigma s_i/N}$:	**1.00**					

Scenario 2: Minimum Initial Proficiency						
	Time					
	Month 1	*Month 2*	*Month 3*	*Month 4*	*Month 5*	*Month 6*
Position 1 (p_1)	1/6	1/3	1/2	2/3	5/6	1
Position 2 (p_2)	1/6	1/3	1/2	2/3	5/6	1
Position 3 (p_3)	1/6	1/3	1/2	2/3	5/6	1
Position 4 (p_4)	1/6	1/3	1/2	2/3	5/6	1
Position 5 (p_5)	1/6	1/3	1/2	2/3	5/6	1
$\Sigma s_{i,m}$:	0.83	1.67	2.50	3.33	4.17	5.00
$\Sigma s_{i,m}/N_m$:	0.17	0.33	0.50	0.67	0.83	1.00
$\boldsymbol{\Sigma s_i/N}$:	**0.58**					

Scenario 3: Distributed Initial Proficiency						
	Time					
	Month 1	*Month 2*	*Month 3*	*Month 4*	*Month 5*	*Month 6*
Position 1 (p_1)	2/3	5/6	1	1	1	1
Position 2 (p_2)	1/6	1/3	1/2	2/3	5/6	1
Position 3 (p_3)	1	1	1	1	1	1
Position 4 (p_4)	1	1	1	1	1	1
Position 5 (p_5)	5/6	1	1	1	1	1
$\Sigma s_{i,m}$:	3.67	4.17	4.50	4.67	4.83	5.00
$\Sigma s_{i,m}/N_m$:	0.73	0.83	0.90	0.93	0.97	1.00
$\boldsymbol{\Sigma s_i/N}$:	**0.89**					

FIGURE 4
Capacity Profiles for Zero-Turnover Conditions



interplay of the aforementioned properties. This measure, combined with "fractional spins"—i.e., site values for which the absolute value of a given member's proficiency is less than one—allows individual-specific proficiencies to be modeled dynamically and combined to capture the overall functional ability of a given collective. The result is a finer-grained picture of how fluctuations at the individual level compile to generate unit-level human and social capital accumulations that drive collective performance effects.

Applying this methodology to the foregoing examples demonstrates how this approach to modeling collective function over time can uncover heretofore overlooked effects stemming from both proficiency accumulation and capital flows. Returning to Scenarios 1 through 3, the shaded circles are replaced by numerical values corresponding to the proficiency accumulations accordant with a given individuals' experience within the collective (note that for the sake of the

FIGURE 5
Capacity Calculations for 100% Turnover Conditions

Scenario 4: Isolated Churn

	Time					
	Month 1	*Month 2*	*Month 3*	*Month 4*	*Month 5*	*Month 6*
Position 1 (p_1)	1/2	2/3	5/6	1	1	1
Position 2 (p_2)	1/2	2/3	5/6	1	1	1
Position 3 (p_3)	1/2	2/3	5/6	1	1	1
Position 4 (p_4)	1/2	2/3	5/6	1	1	1
Position 5 (p_5)	- 1/2	- 1/6	- 1/6	1/6	- 1/6	- 1/6
$\Sigma s_{i,m}$:	1.50	2.50	3.17	4.17	3.83	3.83
$\Sigma s_{i,m}/N_m$:	0.30	0.50	0.63	0.83	0.77	0.77
$\boldsymbol{\Sigma s_i/N}$:	0.63					

Scenario 5: Distributed Churn

	Time					
	Month 1	*Month 2*	*Month 3*	*Month 4*	*Month 5*	*Month 6*
Position 1 (p_1)	- 1/2	1/6	1/3	1/2	2/3	5/6
Position 2 (p_2)	1/2	- 1/2	1/6	1/3	1/2	2/3
Position 3 (p_3)	1/2	2/3	- 2/3	1/6	1/3	1/2
Position 4 (p_4)	1/2	2/3	5/6	1	-1	1/6
Position 5 (p_5)	1/2	2/3	5/6	1	1	-1
$\Sigma s_{i,m}$:	1.50	1.67	1.50	3.00	1.50	1.17
$\Sigma s_{i,m}/N_m$:	0.30	0.33	0.30	0.60	0.30	0.23
$\boldsymbol{\Sigma s_i/N}$:	0.34					

Scenario 6: Mass Exodus

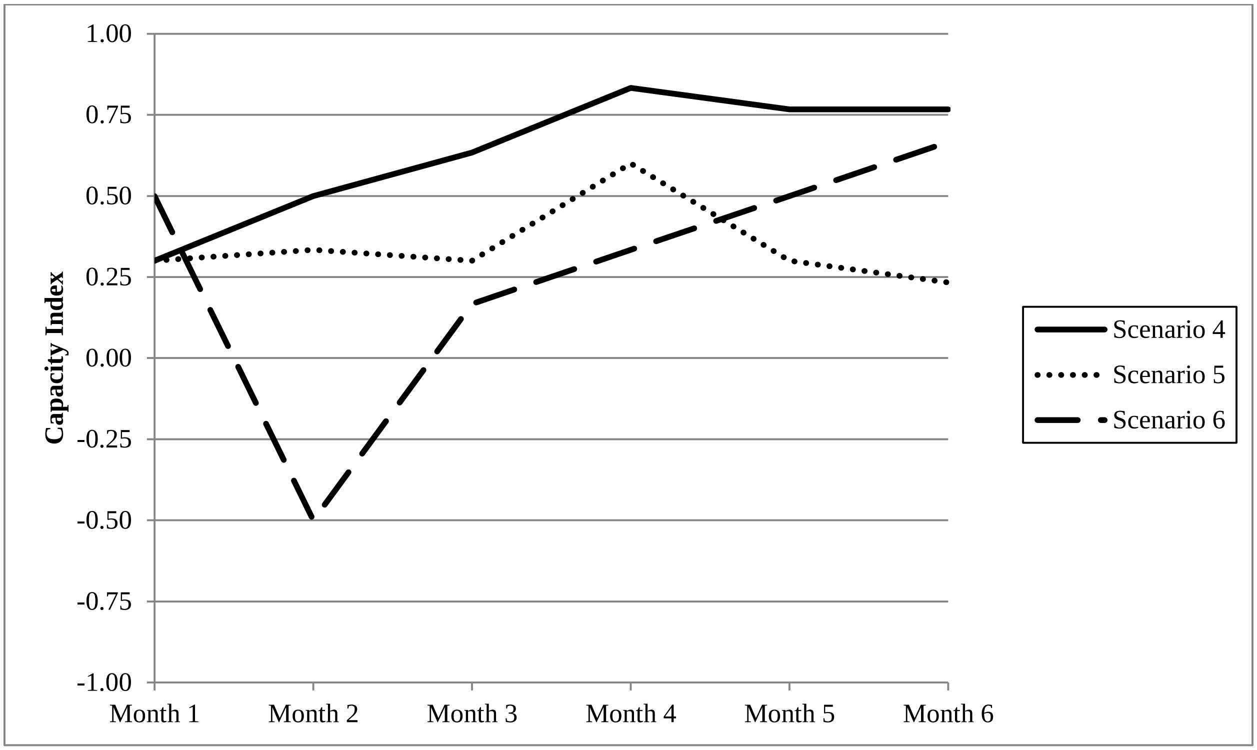
	Time					
	Month 1	*Month 2*	*Month 3*	*Month 4*	*Month 5*	*Month 6*
Position 1 (p_1)	1/2	- 1/2	1/6	1/3	1/2	2/3
Position 2 (p_2)	1/2	- 1/2	1/6	1/3	1/2	2/3
Position 3 (p_3)	1/2	- 1/2	1/6	1/3	1/2	2/3
Position 4 (p_4)	1/2	- 1/2	1/6	1/3	1/2	2/3
Position 5 (p_5)	1/2	- 1/2	1/6	1/3	1/2	2/3
$\Sigma s_{i,m}$:	2.50	-2.50	0.83	1.67	2.50	3.33
$\Sigma s_{i,m}/N_m$:	0.50	-0.50	0.17	0.33	0.50	0.67
$\boldsymbol{\Sigma s_i/N}$:	0.28					

current discussion, it is assumed that an individual requires six months to become proficient at his or her job; see *Figure 3*). As one might expect, the collective depicted in Scenario 1 has the best overall capacity figure ($\sum_i s_i/N = 1.00$) given its full proficiency for the entire observation period while that depicted in Scenario 2 is the least well off ($\sum_i s_i/N = 0.58$) given that its members begin the observation period with minimal levels of proficiency—i.e., all are new hires. Landing in the middle is the collective depicted in Scenario 3 ($\sum_i s_i/N = 0.89$) with distributed initial proficiency levels reflecting a mix of experienced and novice employees. Notably, as *Figure 4* makes clear, what is commonly conceived of as a "stock" of collective capital is, in fact, dynamic and longitudinal in nature even when collective membership remains stable over time due to the tenure-based accumulation of proficiency.

In addition, the capacity index captures the differences in organizational capital accumulations implied by different patterns of employee outflows and, in so doing, is better attuned to fluctuations that, in this case, occur largely as the result of member departures (see *Figure 5*). Specifically, Scenario 6, where the greatest negative impacts are expected, yields a capacity figure of 0.28; Scenario 5, with repeated departures of relatively proficient members yields an index value of 0.34. Finally, Scenario 4, which possesses and maintains a stable core of employees despite the same absolute amount of turnover yields an index value of 0.63.

Thus, as demonstrated by these examples, collectives with identical nominal employee outflows (i.e., separation or instability rates; separation rates for Scenarios 4-6 all equal 100%) may have drastically different capacities for collective performance, essentially addressing some of the concerns set forth by Price (1977) regarding the length of service of remaining and departing employees and "losses relative to in-role performance or human capital" considered by Shaw (2011: 205). Further, the capacity perspective more specifically depicts how collective-

FIGURE 6
Capacity Profiles for 100% Turnover Conditions



level performance effects may arise from various configurations of individual departures and/or proficiency accumulations and how these effects may change over time (see *Figure 6*).

CHAPTER 2

PRODUCTIVE CAPACITY AND PERFORMANCE

Inherent in many, if not all, of the aforementioned related constructs is the assumption that stable membership is a necessary, but not sufficient, condition for the development and maintenance of organizational capital. For instance, stable membership may generate performance benefits for a variety of reasons surrounding enhancements to coordination, knowledge sharing, group learning, familiarity, recognition of expertise and the development of shared mental models (Harris, McMahan, & Wright, 2012). Conversely, unstable membership leads to process losses (Steiner, 1972) as remaining members compensate for performance deficits and focus on non-germane tasks (McGrath, 1991) not directly aimed toward immediate performance. Specifically, member change generates disruption that de-stabilizes coordinating mechanisms and processes, for instance, in the form of redundant efforts or illogical organization of collective activities, ultimately detracting from collective performance (Summers et al., 2012).

Additionally, unstable membership may disrupt social capital within collectives, thus portending exponential versus additive performance losses (Dess & Shaw, 2001; Shaw, Duffy, Johnson, & Lockhart, 2005). The capacity-based approach simultaneously considers both of these dynamics—i.e., the accumulation and degradation of organizational capital over time. When productive capacity is high, the level of accumulated organizational capital within collectives is also likely to be high. Conversely, when productive capacity is low, that level will similarly be low and, further, may be indicative of high levels of resource depletion as a result of changes in collective membership (note that an inexperienced collective with little disruption would also possess low capacity).

At the collective level, accumulated organizational capital, as captured by capacity, is arguably one of the most proximal determinants of unit-level performance, although general human capital remains important as an input to its development (Ployhart et al., 2011). Specifically, capacity accrues partially as a result of collective on-the-job experience and leads to unit-level improvements in the efficiency with which work tasks are completed, the level of service provision to customers, and the quality and quantity of deliverables generated by collectives (Argote & Epple, 1990; Adler & Clark, 1991; Argote et al., 1995; Reagans et al., 2005). These improvements, in turn, should increase customer satisfaction and retention as well as drive profitability and sales (Ployhart et al., 2011; Heskett et al., 1994).

Unsurprisingly, constructs related to productive capacity, and its human and social capital components, have been theorized to relate positively to performance. Towards the human capital side, shared mental models, which emphasize "common cognitive elements among group members" (Ilgen et al., 2005: 525) are argued to generate positive effects on performance by facilitating coordination (Cannon-Bowers & Salas, 2001), thus improving the efficiency and effectiveness with which collective tasks are accomplished (Ilgen et al, 2005; DeChurch & Mesmer-Magnus, 2010). As Mohammed and Dumville (2001: 89) state, "The general thesis of the shared mental model literature is that team effectiveness will improve if team members have an adequate shared understanding of the task, team, equipment, and situation." In short, these collective resources are likely to emerge, in part, through stable collective membership over time and thus, be captured by productive capacity. Also akin to capacity is team learning, which facilitates greater flexibility in team actions and encourages team-process refinement by locating and correcting inefficiencies and errors (Bell & Kozlowski, 2003). As Edmondson (1999: 354) states, “if feedback seeking, experimentation, and discussion of errors individually promote effective performance, learning behavior—which includes all of these activities—is also likely to facilitate performance, whether for individuals or teams.”

Similarly, broad conceptions of social capital also suggest positive performance effects arising from effective its development. In line with concepts of team learning and collective learning curves, social capital requires time and membership stability to develop effectively (Soda, Usai, & Zahee, 2004). Given sufficient development, social capital facilitates knowledge sharing and tacit information transfer within collectives (Nahapiet & Ghoshal, 1998; Adler & Kwon, 2002; Coleman, 1988). Similar to team learning, but possessing a stronger relational element and a greater reliance on undergirding social capital, are constructs relating to group experience.

For instance, Littlepage et al. (1997: 142) posit that group experience leads to enhanced group performance through increases in the accuracy of collective members’ perceptions of expertise held by others as well as through improved utilization of that expertise. Along the same lines, Harrison et al. (2003: 637) argue that member familiarity “facilitate[s] interpersonal attraction and cohesiveness” (637), reduces member uncertainty and anxiety with respect to social relationships, aids development of collective-relevant cognitive structures pertaining to member roles and other characteristics, and encourages higher levels of trust and mutual expectations while abetting potential process losses (640), all of which benefit collective performance. Similarly, Reagans et al. (2005) propose that experience working together positively predicts collective performance as a result of greater coordination among collective members as well as higher accuracy and sophistication of knowledge about fellow members. In the same vein, Huckman and Pisano (2006) argue that familiarity serves as a proxy for accumulated tacit knowledge and positively affects collective performance through improvements to members' communicative abilities.

While some capacity-related constructs appear more or less reliant on forms of human or social capital, respectively, others appear to rest across both capital domains more equally, thus blurring the line delineating these capital forms' respective contributions to organizational capital (Nahapiet, 2012). Specifically, transactive memory "encompasses both the knowledge uniquely held by particular group members with a collective awareness of who knows what" (DeChurch & Mesmer-Magnus, 2010: 33) and presents a prime example of organizational capital (Spender, 2009) due to its dual reliance on (i) collective human capital that is distributed and varies in content across individuals and (ii) the social capital that allows such distributed knowledge to be effectively leveraged. As Bell and Kozlowski (2003: 348) note, "a transactive memory system reduces cognitive load, provides access to an expanded pool of expertise, and decreases redundancy of effort." Thus, to the extent that such systems are well developed, collective performance should be improved. At a higher level of specificity, Austin (2003) examined facets of transactive memory pertaining to the stock, specialization, consensus, and accuracy of collective knowledge and related them to performance within continuing organizational groups. Austin argues:

> Group knowledge stock increases group performance by minimizing the group's need to seek external assistance, transactive memory consensus increases group performance by reducing coordination miscues, knowledge specialization increases group performance by reducing knowledge search, and transactive

memory accuracy increases group performance by enabling correct use of available knowledge resources (868).

Empirical work has broadly supported theoretical arguments surrounding these constructs. Returning to concepts related most directly to human capital, Ployhart, Van Iddekinge, and MacKenzie (2011) found that firm-specific collective human capital correlated positively and significantly to both customer satisfaction ($r = .25$; $p < .05$) and profit ($r = .25$; $p < .05$) in a restaurant chain. Further, they found support for a proposed causal path in which collective human capital positively predicted customer satisfaction ($\beta = .88$; $p < .05$) which, in turn, predicted profit ($\beta = .54$; $p < .05$). Marks, Sabella, Burke, and Zaccaro (2002), found that shared mental models positively influenced team performance through the mediating constructs of coordination—"the process of orchestrating the sequence and timing of interdependent actions" (5)—and backup processes—"assisting team members in performing their tasks" (6) in two experiments involving undergraduate students' performance on an Apache helicopter simulation. In both experiments, the similarity ("sharedness") of mental models correlated positively and significantly with team performance (Study 1: $r = .34$; $p < .05$, Study 2: $r = .30$; $p < .05$). Further, the shared-mental-model-to-performance relationship was completely mediated by coordination and backup processes.

Other work by Mathieu and colleagues (2000) employed a simulation based on the F16 aircraft and used a repeated measures multiple regression path analysis to find evidence of mediation of the mental-model-to-performance relationship such that both team ($\beta = .26$; $p < .05$) and task ($\beta = .31$; $p < .05$) mental models significantly and positively predicted changes in coordination, which itself predicted team performance ($\beta = .49$; $p < .05$). Finally, a recent meta-analysis (DeChurch & Mesmer-Magnus, 2010) of the cognitive bases of effective teamwork considered shared mental models and found a positive and significant corrected mean correlation between shared mental models (operationalized as compositional cognitive constructs) and performance ($\rho = .32$).

Regarding team learning, Edmondson (1999) found evidence that self-reported team learning positively and significantly correlated with externally-rated performance ($r = .53$; $p < .05$) in a manufacturing setting. In addition, self-reported learning predicted performance in a baseline regression model ($\beta = .80$; $p < .01$). Employing a decidedly dynamic perspective, Argote et al. (1995) also found evidence that team learning predicted performance over time in their analysis of learning curves. Using a sample of 240 undergraduates, they found that, on a paper-folding task, a significant increase in the number of "products" created by groups over time occurred, albeit at a decreasing rate of improvement.

With respect to constructs arguably more reliant on social capital elements, research surrounding group learning has also revealed positive relationships with performance. For example, in a study involving 60 undergraduate students completing quizzes pertaining to United States geography, Littlepage et al. (1997) utilized structural equation modeling and found that group experience positively predicted utilization of expertise ($\beta = .49$; p < .05) which itself predicted group performance ($\beta = .87$; p < .05; note that the positive effect of group experience on utilization of expertise was partially mediated by recognition of expertise). Addressing member familiarity, Harrison et al. (2003) performed a longitudinal examination of team performance in terms of speed and quality across a variety of tasks with a sample of undergraduate students over a three-week period. Results of their ANOVA analysis demonstrated that member familiarity generated significant and positive effects in terms of both speed ($F = 6.05$; $p < .05$) and quality of performance ($F = 3.19$; $p < .05$). Similarly, in the context of a teaching hospital's orthopedics department, Reagans et al. (2005) found a significant and negative correlation between team experience and completion time for knee and hip replacement procedures (r = -.13; p < .05; i.e., the duration of procedures decreased with familiarity among team members) as well as a negative effect on procedure duration in a full model specification (β = -.022; p < .05). In another surgical context, Huckman and Pisano (2006) focused on the performance of individual surgeons across multiple hospitals and, through sophisticated analyses, found that familiarity with surgical team members explained variance in hospital-specific performance above and beyond the effects of individual influence and quality.

Further, a limited amount of empirical field work has connected transactive memory to collective performance. Austin (2003), examining facets of transactive memory systems, found significant and positive correlations between the specialization (r = .39; p < .05), consensus (r = .52; p < .01), and accuracy (r = .69; p < .01) facets of transactive memory systems and the attainment of financial and developmental goals as evaluated by an external group comprised of three managers and an internal team development specialist. However, these results did not hold up to regression analysis, although overall transactive memory did significantly and positively predict goal attainment as well as internally- and externally-evaluated performance (facet measures were combined into a single index and analyzed with a global F-test).

Other work by Lewis (2003) has also investigated the role transactive memory systems play in facilitating performance. Conducting a study of 27 teams in technology firms, Lewis examined three facets of transactive memory—specialization, credibility, and coordination—and found positive and significant correlations between a composite measure of those facets and team-assessed performance (r = .73; p < .05) as well as performance as rated by managers (r = .57; p < .05). More recent work by DeChurch and Mesmer-Magnus (2010) utilized meta-analysis to investigate the cognitive underpinnings of collective performance and found a positive and significant corrected mean correlation ($\rho = .44$) between performance and transactive memory system quality (operationalized as compilational cognitive constructs).

Further, the role of disruption in affecting collective resources, has also been empirically established. For instance, returning to the concepts of team learning and collective learning curves, Argote and Epple (1990) identify unstable membership as a potential driver of the lack of organizational learning at Lockheed in the 1970s and 1980s with respect to aircraft production. Additionally, Argote et al.'s (1995) paper-folding study indicated a significant main effect for turnover ($F = 9.28$; $p < .01$) on the amount of output produced over time with significant differences in mean unit output between groups with no turnover ($M = 104.95$) and those that experienced turnover ($M = 80.77$).

In their analysis of performance effects stemming from member familiarity, Harrison et al. (2003) found that stable membership within collectives improved performance over time. More specifically, these authors assessed three conditions with respect to member familiarity on teams—"familiar" teams possessed *a priori* familiarity, "continuing" teams lacked *a priori* familiarity but maintained stable membership over the observation period, and "one-shot" teams were composed of new members at each iteration of the study. While familiar teams initially outperformed all others (and always outperformed one-shot teams), by the last iteration, continuing teams had matched familiar teams in terms of the speed and quality of their performance. Similarly, Harrison et al. (2012) found evidence that stability in membership and collective performance were positively related in a sample of NCAA men's basketball teams ($\beta = .22$; $p < .05$).

Also related to disruption, Summers et al. (2012) investigated how member change and flux in coordinating mechanisms affected performance on a marketing simulation in four-member teams of upper-level undergraduate business students. Results revealed a negative and significant correlation between flux and task performance (r = -.27; p < .01); this relationship was also supported in regression analyses (β = -.52; p < .01). Finally, Heavey, Holwerda, and Hausknecht (2013) employed meta-analysis to investigate, among other things, the relationships between collective turnover and salient organizational outcomes. These authors detected significant and negative mean correlations between turnover and customer satisfaction ($\bar{r}$ = -.22), productive efficiency ($\bar{r}$ = -.22), profit margin ($\bar{r}$ = -.15), and sales efficiency ($\bar{r}$ = -.09) as well as a positive and significant mean correlation between turnover and error/loss rates ($\bar{r}$ = .14), all of which suggest that relatively consistent negative collective performance effects arise from persistently unstable membership.

It has been argued that productive capacity, as a form of organizational capital (Spender, 2009), is comprised of and subject to influences from the combination of collective forms of human and social capital as well as alterations imposed on those collective resources by member inflows and outflows. In essence, the construct aims to capture the dynamic accretion and diminution of all the unit-level resources that facilitate collective function. However, to borrow Bliese's (2000) terminology, the "fuzzy" nature of the construct's structure makes it difficult, if not impossible, to delineate where the respective influences of human capital, social capital, and member inflows/outflows start and end (Nahapiet, 2012; Hausknecht & Holwerda, 2013).

Nonetheless, the respective roles that these components play in affecting collective performance have been established theoretically and empirically in the preceding discussion and elsewhere. Thus, if (i) collective-level resources (e.g., shared mental models, team learning, group experience, transactive memory systems) have been theoretically and empirically linked to performance, (ii) disruptions to collective-level resources (e.g., turnover, flux, member change) have been theoretically and empirically linked to performance, and (iii) productive capacity encapsulates all of these things, then (iv) productive capacity should relate to performance. Given these arguments and associated empirical evidence:

Hypothesis 1: Productive capacity will positively relate to collective performance.

CHAPTER 3

THE ROLE OF CONTEXT: COMPLEXITY AS A MODERATOR OF THE PRODUCTIVE CAPACITY-PERFORMANCE RELATIONSHIP

The importance of context—"situational opportunities and constraints that affect the occurrence and meaning of organizational behavior as well as functional relationships between variables" (Johns, 2006: 386)—has long and frequently been recognized, if markedly less studied, in organizational research. As before, while no extant research has examined contextual effects with respect to capacity, work surrounding related constructs has argued for the importance of context regarding their respective relationships with salient organizational outcomes. For instance, work considering member outflows has repeatedly highlighted the role of context in influencing key constructs and the relationships between them. Focusing on turnover, Capelli and Sherer (1991) discuss the role of context as critical in the broad realm of meso-level research, emphasizing the respective roles of the economic environment, changes to and fluctuations of business cycles, and, and most pertinent to the discussion of capacity, constraints that encourage stability of membership within collectives. Focusing within organizations, Schwab (1991) highlights the role of institutional characteristics and organizational processes in affecting turnover-performance relationships. Finally, Cohen and Bailey (1997: 240) identify context as exerting potentially "extremely important" effects on team function and effectiveness[5]. Perhaps most pertinent to the current work, a key contextual variable

[5] I follow Cohen and Bailey (1997: 241) in defining teams broadly as "a collection of individuals who are interdependent in their tasks, who share responsibility of outcomes, who see themselves and who are seen by others as an intact social entity embedded in one or more larger social systems…and who manage their relationships across organizational boundaries." In keeping with this perspective, teams are envisioned as possessing at least some

that may influence the strength of the capacity-performance relationship is the complexity inherent in the work environment (Nyberg & Ployhart, 2013). In the case of the units under examination here, complexity is defined primarily by the degree of interdependence associated with two critical components, namely the tasks units perform (task-environment complexity) and the modes of interaction required among participants as a result of task and team configurations (member coordination complexity).

Task-environment complexity refers to the "sequencing of activities in workflow" (Cohen & Bailey, 1997: 133) and, in particular, to the degree to which tasks and activities are interdependent or integrated and the work product is "the end result of numerous contributions or efforts by all group members" (Kozlowski & Bell, 2003: 352) rather than the additive effect of independent efforts. A high degree of interdependence in work units is suggestive of a need for greater communication, cooperation, and collaboration among its members (Ployhart & Moliterno, 2013; Nyberg & Ployhart, 2013; Cohen & Bailey, 1997; Kozlowski & Bell, 2003). For instance, following in the footsteps of pioneering work by Thompson (1967), several authors have developed and refined typologies of collectives based on the levels of task interdependence and complexity inherent in their work (e.g., Van de Ven, Delbecq, & Koenig, 1976; Saavedra, Earley, & Van Dyne, 1993; Kozlowski & Bell, 2003). In particular, these typologies have consistently acknowledged three main modes of task interaction falling along a continuum from situations in which the interactions are unidirectional and collective performance is an additive function to situations in which interactions are bi- or multidirectional and group performance is a multiplicative function of individual inputs.

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minimal degree of interdependence or "groupness" (ibid.). Thus, a group of employees (e.g., call center employees working independently within a department or an accounting department in which work is organized along purely functional lines but carried out independently at the employee level) would not qualify as a team. Rather, in the current discussion, minimal interdependence is assumed but expected to vary in degree in meaningful way across units of analysis.

At the additive end of the spectrum lie collectives conforming to pooled interdependence in which “each member makes a contribution to group output without the need for direct interaction among members” (Saavedra et al., 1993: 62). Such collectives are characterized by the presence of similar (or identical) member roles and, often, by a single individual completing the “entire” task under consideration. More complex, and/or interdependent, are those collectives falling under the rubric of sequential interdependence where “one group member must act before another can act” (ibid.). Under this interaction mode, member roles are differentiated and segments of the group task are performed in an externally imposed order. Alternatively, such interactions may be viewed as “producer/consumer relationships” in which “one activity produces something that is used by another activity” (Malone & Crowston, 1994: 93). At the “most interdependent” end of the spectrum lie teams falling under reciprocal interdependence in which “Person A’s output becomes Person B’s input and vice versa” and workflow is “characterized by temporally-lagged, two-way interactions” (Saavedra et al., 1993: 63). Once more, member roles are differentiated but workflow is flexible in nature as opposed to being externally and sequentially ordered.

As an example of these various forms of interdependence and modes of interaction, one may consider the provision of web development services, particularly along the lines of sales, website design, and search engine optimization functions. Under a mode of pooled (low) interdependence, one might observe individually specialized employee-client relationships in which all three functions are handled by a single employee, although multiple employees—for instance, three—may be housed within a web design firm or department. Under the increasing complexity of (mid-level) sequential interdependence, work would fall into specialized roles in which sales of the service would occur first by one employee, design of the website itself would occur by a second, and finally, the completed website would be optimized to maximize search engine results by a third. Such organization would typify the aforementioned producer/consumer relationships in which one employee's output serves as the next employee's required input. Under reciprocal interdependence (and high-level complexity), the same functions would be performed, but rather than occurring sequentially, various specialist employees would perform their respective work simultaneously, for instance selling specialized designs and optimization strategies or tailoring designs to proposed optimization techniques and goals. Workflow progression from pooled through sequential to reciprocal forms increases the degree of task-environment complexity involved.

A second form of complexity, member coordination complexity, refers to the configuration-based intricacy of social connections that occur in the workplace or "the additional complexity that needs to be taken into account when the task is carried out collaboratively" (Espinosa, Slaughter, Kraut, & Herbsleb, 2007: 626). As Espinosa and colleagues contend:

> [A] task can have a certain inherent level of complexity due to its size and structure. However, this same task can become more complex depending on how many people work on it and how these people are configured (613).

In particular, certain within-unit configurations of people suggest important influences on the demand for and the ease of communication, cooperation, and collaboration. As an example, one can consider two teams of identical size performing identical product development functions within separate and distinct organizations. In "Autonomous" Organization A, the collective is organized as a cross-functional and semi-autonomous project team with its members possessing the necessary KSAOs and decision-making ability (or supervisory oversight) locally with the team. In "Red-Tape" Organization B, the collective, although co-located geographically, lacks localized decision-making ability or supervisory oversight. Rather, decisions and actions are bound within functional silos and subject to supervisory approval at a distance from the team itself.

In the autonomous organization, member coordination complexity is low as interactions can occur purely along functional/efficiency lines. In the red-tape organization, however, coordination complexity is considerably higher as the management of mutual dependencies (Malone & Crowston, 1994) becomes more difficult, and thus places greater demands on the collective capabilities of the team for their successful navigation. In essence, the ability of team members to communicate, cooperate, and collaborate is obstructed by inefficient configuration and such configuration "makes it challenging for individual members to get acquainted with their colleagues' work skills and habits, identify and access expertise when needed, develop task, presence and contextual awareness, and manage their respective task dependencies" (Espinosa et al., 2007: 614). Thus, the configuration of members within a team, itself, may also increase the complexity it faces.

It is argued here that such differences in complexity will moderate the relationship between productive capacity and performance with the anticipated relationship being stronger in more complex, as opposed to less complex, work environments. These differences are theorized to arise as a result of changing demands for: (i) communication—task- or teamwork-related information exchange focusing on solving problems or "establishing patterns of interaction and enhancing their quality" (Kozlowski & Bell, 2003: 353); (ii) cooperation—"the willful contribution of personal efforts to the completion of interdependent jobs" (Wagner, 1995: 152); and (iii) collaboration—"activities required to manage interdependencies with the team work flow" centering on concerted integration of member actions and simultaneity constraints

(Kozlowski & Bell, 2003; Malone & Crowston, 1994). Such demands co-vary with the level of complexity or interdependence inherent in a given work environment. Put simply, "as task interdependence increases, the requirements for coordination, communication, and cooperation also increase for work units to perform well" (Saavedra et al., 1993: 61). More specifically, as Bell and Kozlowski (2002) assert:

> …less complex tasks often require minimal communication and collaboration between team members. Team performance is either an additive function of individual performance or the result of unidirectional interfaces between team members…As tasks become more complex, they necessitate more precise forms of coordinated effort. Team members' roles become highly interdependent and the need for well-orchestrated teamwork, reciprocal communication, and feedback is essential. Communication and collaboration demands increase dramatically, and information richness becomes critical (24-25).

As work environment complexity increases and the necessity for precise and sophisticated interaction increases, the strength of the relationship between collective resources that enable such interaction and performance should also increase.

Most pertinent to the current investigation, and regardless of the level of work environment complexity, increases in productive capacity should lead to more frequent, sophisticated, and effective levels of communication, cooperation, and collaboration. This is based on relationships theorized and found for related constructs. Increases in productive capacity suggest increases in the availability and sophistication of collective resources (e.g., knowledge sharing, team learning, group familiarity, shared mental models, transactive memory systems, cross-understanding) that are relational in nature and take time to develop. As productive capacity increases, so should resources that drive effective communication, cooperation, and collaboration and, ultimately, performance. The development of such resources may or may not be contingent on work environment complexity, although the paths by which development occurs and the time necessary to reach full proficiency may vary depending upon the level of complexity involved.

In particular, the benefits of productive capacity are more likely to accrue in more complex work environments for two reasons. First, the sophisticated interactions that high capacity enables are more central to performance in more complex environments. That is, productive capacity engenders the higher levels of communication, cooperation, and collaboration that more complex work environments require. Second, the reciprocal nature of connections within such collectives allows for feedback loops that generate synergistic and multiplicative performance effects. By comparison, less complex work environments involve fewer connections that are less rich and/or elaborate in nature and, thus, create lower demands for communication, cooperation, and collaboration. In these situations, such collective resources are (i) less central to driving collective performance and (ii) less likely to exert multiplicative effects on performance given the underlying number, patterns, and nature of intra-collective connections—i.e., the theorized productive-capacity-to-performance relationship is muted. Thus, a one-unit increase in productive capacity is likely to produce a greater performance effect in more, versus less, complex work environments.

Several meta-analyses support the broader contention that complexity moderates the relationship between collective resources and performance. For instance, Gully, Devine and Whitney (1995) argued that cohesion should be especially important in complex work environments as, in such environments, it serves to affect group processes and group outcomes as well as individual motivational factors. By comparison, these authors suggest that in low-complexity environments, cohesion might affect only individual motivation and thus, exert little influence on group-level processes and outcomes as “there is little need for the group to coordinate, communicate, or cooperate” (502). As expected, these authors found evidence that the cohesion-performance relationship was stronger under conditions of higher complexity. Gully, Incalcaterra, Joshi, and Baubien (2002) found similar results with respect to the relationship between collective-efficacy—“a shared belief in a collective’s capabilities to organize and execute courses of action” (820)—and performance. More recently, LePine et al. (2008) focused on the greater number and intricacy of within-collective connections in high-complexity environments, as compared to lower-complexity environments, as the theoretical mechanism by which complexity moderated the relationship between teamwork processes and performance. Their meta-analysis supported these contentions.

Beyond meta-analyses, Espinosa et al. (2007) conducted primary work investigating the role of still another collective resource, team familiarity, in driving performance. They predicted that group familiarity’s positive effects on performance would be stronger in situations with higher team coordination complexity—operationalized by geographic dispersion—as it would help team members overcome the difficulties associated with greater communication, cooperation, and collaboration needs associated with complex within-team configurations. As expected, they found that, among software development teams, there was a significant interaction term between geographic dispersion and group familiarity when it came to predicting performance.

To test whether similar dynamics are at work in the units studied here, I examine the extent to which workplace complexity moderates the relationship between productive capacity and unit performance. Since task-environment complexity is relatively constant across these work units due to standardized modes of organization and procedures, I focus on team coordination complexity and, more specifically on two dimensions of team coordination complexity: unit size and workforce diversity.

Unit Size

As unit size—defined here as the number of members in a unit (Nieva, Fleishman, & Reick, 1985; Hill, 1982)—increases, it should increase the challenges surrounding effective communication, cooperation, and collaboration. While larger units may have greater access to resources, they also suffer from communication difficulties as the number of dependency links among members increases. This is associated with impediments to cooperation and collaboration due to breakdowns in leader-member exchanges, reduced team cohesion, and related process-based inefficiencies (Latané, Williams, & Harkins, 1979; Green, Anderson, & Shivers, 1996; Terborg & Lee, 1984; Price, 1977; Campion, Medsker, & Higgs, 1993; Steiner, 1972; Hausknecht et al., 2009; Gersick & Hackman, 1990; Espinosa et al., 2007; Steiner, 1966; Hill, 1982; Bell & Kozlowski, 2003; Hausknecht et al., 2009).

Leenders, van Engelen, and Kratzer (2003), for example, investigated the relationship between unit size and communication effectiveness in new product development teams and found a significant relationship between the two. Curral, Forrester, Dawson, and West (2010) also examined the relationship between unit size and team processes across four domains—clarity of and commitment to team objectives, participation levels, support for innovation, and emphasis on quality—in a cross-industry study of 87 teams in Portugal. Citing process losses specific to larger as opposed to smaller units, they predicted and found evidence that unit size related negatively to all four team process variables (r = -.22 to -.33; $p < .01$). Finally, Stahelski and Tsukuda (1990) investigated interdisciplinary teams within a medical center and found that prosocial behavior declines in larger units. Specifically, as unit size increased, cooperation among members decreased (β = .57; t =-4.35; p = .001).

Other recent studies support the moderating effects of unit size. For instance, Espinosa et al. (2007) examined size as a moderator of the relationship between team familiarity and performance. They reasoned that increases in unit size lead to higher performance-relevant demands for familiarity but that these become more difficult to meet due to an exponential increase in the potential number of dyadic connections within units and the difficulties surrounding efficient knowledge transfer in larger units. Their results showed that, as hypothesized, familiarity had stronger positive performance effects in larger units (β = .106; p = .002 for team familiarity × team size interaction). In a similar vein, LePine et al. (2008) suggested that size moderates the relationship between teamwork processes and collective performance based on the idea that larger units are more subject to coordination difficulties as a result of having more linkages and, therefore, are more reliant on effective teamwork processes to overcome such difficulties. Employing meta-analytic techniques, they found that the teamwork-process-to-performance relationship was significantly stronger in larger units (β = .03; $p < .05$, one-tailed) than in smaller teams. Taken together, these studies reveal an underlying logic that increases in unit size lead to greater needs for enhanced communication, cooperation, and collaboration and that increases in productive capacity should help to meet these needs. Given extant theory and research, then:

Hypothesis 2: Unit size will moderate the positive relationship between productive capacity and performance such that productive capacity will be a stronger predictor of performance in larger, versus smaller, collectives.

Diversity

Another key contextual factor, especially salient to many organizations today (Pieterse, Van Knippenberg, & Dierendonck, 2013; Mannix & Neale, 2005), is within-collective diversity—"*the distribution of differences among the members of a unit with respect to a common attribute, X, such as tenure, ethnicity, conscientiousness, task attitude, or pay*" (Harrison & Klein, 2007: 1199; italics in original). While considerable research has focused on the topic of diversity (e.g., Williams & O'Reilly, 1989; Milliken & Martins, 1996; Webber & Donahue, 2001; Alderfer & Sims, 2003; Jackson, Joshi, & Earhardt, 2003; Mannix & Neale, 2005; van Knippenberg & Schippers, 2007; Horwitz & Horwitz, 2007; Harrison & Klein, 2007; Stahl, Maznevski, Voigt, & Jonsen, 2009; Joshi & Roh, 2009; Bell, Villado, Lukasik, Belau, & Biggs, 2011), relatively little of it relates directly to the issue of team coordination complexity.

Nonetheless, there is some reason to believe that diverse collectives possess a rich assortment of knowledge, but also face significant challenges with respect to the common harnessing of this knowledge and the development of the common understandings that are essential for effective communication, cooperation, and collaboration (Harrison et al., 2002; Mannix & Neale, 2005; Milliken & Martens, 1996; and Williams & O'Reilly, 1989). Further, conditions of separation or social categorization (Byrne, 1971; Tajfel & Turner, 1979; Pfeffer, 1983) suggest the formation of subgroup boundaries that impede communication. Thus, cooperation and coordination must occur along idiosyncratic social boundaries as well as along functional lines, complicating the work environment. Further, social categorization impedes "organizational members from engaging in cooperative behaviors" (Richard, Murthi & Ismail, 2007: 1215) while also engendering "potential conflict across cohort groups" (Pfeffer, 1983: 335).

These contentions are consistent with extant research. For instance, Zenger and Lawrence (1989) investigated the linkage between diversity and communication frequency. Working from the perspective that "demographic attributes such as age, tenure, occupation, and gender provide surrogate measures for the common experiences that shape language development" and that "differences in background and experience may result in language differences that constrain communication among employees" (356), these researchers found that similarity (i.e., homogeneity) with respect to age ($r = .43$; $p < .001$) and tenure ($r = .30$; $p < .01$) were associated with communication frequency. In a full model specification predicting communication, the effect of tenure similarity did not hold ($\beta = -.01$; NS), although age similarity remained a significant predictor ($\beta = .038$; $p < .05$).

In a similar vein, Stahl and colleagues (2009) meta-analyzed a sample of 108 empirical studies and determined that surface-level diversity was associated with lower effectiveness of communication ($\bar{r} = -.16$; $p < .05$), higher levels of conflict ($\bar{r} = .08$; $p < .05$), and lower levels of social integration ($\bar{r} = -.06$; $p < .10$), although the latter effect was only marginally significant. Also considering social integration, O'Reilly, Caldwell, and Barnett (1989) examined 79 field representatives across 20 work units within a large convenience store chain and found a negative association between tenure diversity and social integration ($r = -.54$; $p < .05$). Ely (2004) investigated the effects of racial/ethnic and tenure diversity on team processes measured as an index consisting of frequency of open discussion, cooperation, comfort in working together, and teamwork quality in 486 retail bank branches and found a negative and significant association between the two ($r = -.11$; $p < .05$).

In addition, Harrison and colleagues (2002) found that measures of actual racial/ethnic diversity ($r = -.18$; $p < .05$) and perceived surface-level diversity ($r = -.41$; $p < .01$) were associated with lower levels of social integration in a sample of 562 students performing business-related tasks. Fisher et al. (2012), proposed that higher levels of racial and gender diversity in teams would be negatively related to mental model similarity. They found that racial diversity negatively predicted mental model similarity ($\beta = -.73$; $p < .01$) but failed to find a significant relationship between gender diversity and mental model similarity ($\beta = -.21$; $p = .17$). They also found that mental model similarity positively related to implicit team coordination ($\beta = .34$; $p < .05$) defined as "providing task-relevant information to other team members without a specific request, proactively sharing workload and helping other team members, monitoring other team members' activities and performance, and adapting behaviors in anticipation of others actions" (830). Finally, implicit coordination was found to positively predict performance ($\beta = .40$; $p < .05$) and, most important, implicit coordination mediated the mental-model-performance relationship (95% CI for indirect effect: [0.09, 14.51]).

Taken together, these results provide evidence that diversity may generate greater complexity within collectives in the form of increased demands for greater communication, cooperation, and collaboration. They also suggest that enhanced collective resources or organizational capital, in this case in the form of productive capacity, may be critical for meeting these demands and, thus, overcoming the process inefficiencies involved. Thus:

Hypothesis 3a: Collective age diversity will moderate the positive relationship between productive capacity and performance such that productive capacity will be a stronger predictor of performance in more heterogeneous, versus less heterogeneous, collectives.

Hypothesis 3b: Collective tenure diversity will moderate the positive relationship between productive capacity and performance such that productive capacity will be a stronger predictor of performance in more heterogeneous, versus less heterogeneous, collectives.

Hypothesis 3c: Collective ethnic diversity will moderate the positive relationship between productive capacity and performance such that productive capacity will be a stronger predictor of performance in more heterogeneous, versus less heterogeneous, collectives.

Hypothesis 3d: Collective gender diversity will moderate the positive relationship between productive capacity and performance such that productive capacity will be a stronger predictor of performance in more heterogeneous, versus less heterogeneous, collectives.

CHAPTER 4

METHODS

Sample and Data

The sample population consists of a random sample of 400 units[6] of a large U.S.-based service organization falling within the accommodation and food services classification of the North American Industry Classification System (NAICS)—i.e., those "establishments providing customers with lodging and/or preparing meals, snacks, and beverages for immediate consumption" (www.bls.gov). Such a sample size is sufficient to detect interaction effects should they exist. For instance, Cohen, Cohen, West, and Aiken (2003) indicate that a sample size of 392 is sufficient to detect a small effect size interaction (that is, a squared partial correlation of .02) and a sample size of 55 is sufficient to detect an interaction effect size (i.e., a squared partial correlation) of .13.

Statistical power is a function of three primary factors—the significance level (α) of the test, the sample size involved in the analysis—which is especially critical in tests of moderated multiple regression (Aguinis, 1995)—and the magnitude of the true effect as it exists in the sample population (Aiken & West, 1991; Faul, Erdfelder, Lang, & Buchner, 2007). Reliability is a key consideration informing the size of the random sample from which data are drawn. In the organizational sciences, measurement of predictors is seldom error-free and reliabilities in the range of .80 are often considered desirable (Cohen et al., 2003). However, for the data at hand, reliabilities of predictors are likely higher than is often the case in much organizational or social science research. Specifically, with the exception of one criterion variable, customer satisfaction,

[6] At the request of the partner organization, a random sample is taken to protect the organization's anonymity.

establishment-level data are objective in nature and thus, less subject to measurement error. Further, demographic data that are aggregated from individual responses to form establishment-level variables—e.g., age, ethnicity, and gender—are, by their nature, considered accurate in the form of self-reports and should exhibit "close to perfect" reliabilities (Cohen, et al., 2003). Finally, given that all data were acquired from a relatively advanced and computerized database (e.g., specific hire dates for individual employees are known), unreliability in measurement does not a appear to be a significant risk although perfect reliability of measures is not assumed.

Given these considerations and (i) that effect sizes in the social sciences generally fall within the small-to-medium range (i.e., b = .02 - .15; Cohen, 1988) and (ii) that with a reliability of .80 (which is likely lower than would be expected in the data in the current investigation) and a significance level of $\alpha = .05$, a sample size of 392 is sufficient to detect small effect sizes in moderation analyses (Cohen, 1988; Aiken & West, 1991; Cohen et al., 2003), a random sample of 400 establishments is employed in the following analyses. Further, given evidence that the moderators under investigation here are continuous and thus, free from concerns regarding unequal sample size across subgroups (Aguinis, 1995), a sample size of 400 appears sufficient to detect the aforementioned predicted effects. Finally, *a priori* power analyses conducted with G*Power 3 (Erdfelder, Faul, & Buchner, 1996) indicate that a sample size of 400 would be sufficient to detect an effect size as small as b = .027 and thus, likely to detect the predicted effects in the current analysis. All data were obtained from archival records kept by the company and correspond to the years 2010 and 2011 (i.e., the partner organization's operating fiscal year).

Focal Variable Measures

Productive capacity. Following Hausknecht and Holwerda (2013), productive capacity was calculated on a monthly basis according to the procedures outlined previously. Specifically, three pieces of information were used to calculate capacity—employee start date, employee quit date (if applicable), and time-to-proficiency, or the time necessary to become proficient at one's job. Interviews with top human resources managers within the partner organization indicated that, on average, time-to-proficiency was six months across all positions considered in the sample. Thus, an employee who had been employed for one month received a proficiency figure of 1/6; an employee who had been employed for two months received a proficiency figure of 1/3; an employee who had been employed for three months received a figure of 1/2; an employee who had been with the organization for four months received a figure of 2/3; and an employee who been with the organization for five months received a figure of 5/6. All employees who had been continuously employed for six months or longer received a proficiency figure of 1. In the event of a quit or other employee departure, the employee received a score equal to his or her current proficiency multiplied by -1 for that month. For instance, if an employee who had worked for the organization for three months quit, he would receive a score of -1/2 for that month. All new hires were assumed to enter the organization with minimum proficiency—i.e., a value of 1/6—and entered into unit productive capacity calculations during the month of their respective hire dates. After individual-level proficiency figures were assigned, the figures were summed and divided by the total unit size according to the formula:

$$\text{Capacity Index} = (\textstyle\sum_i s_i)/N.$$

This operation yields monthly capacity figures. After this, the mean of these figures across a fiscal year, within collectives, was taken to generate annual average capacity figures by collective.

Unit size. Unit size was measured as the total number of employees receiving pay within a given fiscal month. As before, the mean of monthly values was taken within unit across the fiscal year to generate the average annual unit size.

Diversity. Harrison and Klein (2007: 1200) contend that diversity may exist in one of three forms: *separation* or "differences in position or opinion among unit members," envisioned as falling along a single continuum such as age or tenure; *variety* or "differences in kind or category, primarily of information, knowledge, or experience among unit members" or the degree to which collective members are spread across disparate categories such as race/ethnicity or sex/gender; and, less relevant to the current discussion, *disparity*—"differences in concentration of valued social assets or resources such as pay and status among unit members."[7] Pointing out inconsistencies within the extant literature regarding the match between theory and accordant operationalizations, these authors advise specificity in theorizing about diversity with respect to its predicted form. Following this call, diversity here is operationalized in two, surface-level forms—separation (age and tenure) and variety (ethnicity and gender). Most pertinent to the current discussion, theory surrounding diversity's effects on team functioning suggests uniform effects on task environment complexity regardless of form.

[7] The third type of diversity, disparity stands somewhat apart from the previous two due, in part, to its foundations in the sociological and economics literatures and considers power and possession-based relationships in addition to dispersion with respect to a given attribute. While the disparity-based perspective of diversity does not bear direct relevance to the current investigation, it is worth noting that the misapplication of disparity operationalizations (e.g., the Gini coefficient or the coefficient of variation) to separation or variety diversity constructs can lead to distortion of empirical results (see Harrison & Klein, 2007 for specific instances and further discussion).

More specifically, while diversity-performance relationships may vary substantially based on the form of diversity considered, diversity-complexity relationships should not. Given this contention, it may initially appear unnecessary to apply attribute-specific conceptions of diversity to the current investigation (e.g., race, gender, tenure, and age respectively versus a single combined index of diversity). Nonetheless, given that diversity with respect to various specific attributes may possess varying degrees of salience to collective members (Harrison et al., 2002; Bell et al., 2011) and may generate different magnitudes of effects (e.g., one attribute may be salient and increase member coordination complexity while another may not) and that combined indexes of diversity are largely undesirable (Joshi & Roh, 2009; Harrison & Klein, 2007), attribute-specific conceptions are employed here despite their theoretical similarities with respect to effects on the complexity inherent in the work environment.

All demographic (surface-level) diversity data were generated by employee self-reports—that is, employees self-identified as falling into a specific ethnic group as well as specified their own gender and age. Tenure diversity data were generated via calculations based on employee start dates. Following the suggestions of Harrison and Klein (2007), age diversity and tenure diversity were calculated as within-collective standard deviations (see also Nishii & Mayer, 2009). Also following Harrison and Klein (2007), racial/ethnic diversity and gender diversity were calculated using Blau's (1977) index of homogeneity according to the formula:

$$1 - \sum(Pi)^2$$

where *Pi* represents the proportion of collective members falling into the i^{th} category. Once more, all diversity indexes were calculated on a monthly basis within collectives. The mean of monthly values across an entire fiscal year was taken in order to generate annual average values within collectives.

Customer satisfaction. Overall customer satisfaction was measured through the use of customer responses to phone and internet-based surveys. Participation in the survey was encouraged via the chance to win prizes in a monthly sweepstakes for participants. The survey asked respondents to rate their experience with the focal organization on a three-item scale including items for overall experience; likelihood to recommend the establishment to someone else; and product/service quality (α = .90). Scores were reported by the partner organization as the proportion of respondents selecting "5" as the response to each item, with "5" anchored as the highest level of satisfaction (e.g., "excellent" overall experience, "very likely" to recommend to other people, "excellent" product/service quality). Further, confirmatory factor analysis (CFA) utilizing principal axis factoring indicated that all scale items loaded onto a single factor. As a result, scores were averaged within collectives across the fiscal year to obtain average annual customer satisfaction.

Gross sales. Gross sales were measured as the sum of all sales for a given collective in a given month (note that gross sales excludes discounts and returns). As before, gross sales were averaged within collectives across the fiscal year in order to generate average gross sales per month.

Gross sales per customer. Gross sales per customer were calculated on a monthly basis as gross sales divided by number of customers. The mean of these monthly values was taken across the fiscal year to generate average gross sales per customer.

Control Variable Measures

Metropolitan statistical area (MSA) population. The population of the metropolitan statistical area in which a given unit was located was included as a control as units in areas with larger populations may be busier, which may generate effects on gross sales and customer satisfaction. Population data were obtained from 2010 United States Census figures (www.census.gov) and reflect MSA population as of April 1, 2010 (roughly two months prior to the start of the study's observation period).

Unemployment rate. Unemployment rate was included as a control variable in the following analyses as it may generate effects on the propensity of collective members to quit their jobs (a factor central to the calculation of the capacity index) as well as local consumers' willingness to spend money at establishments providing non-essential goods, thus influencing gross sales (e.g., see Hausknecht et al., 2009). Unemployment rates were obtained from records of the Bureau of Labor Statistics (www.bls.gov) and were linked to specific collectives/establishments via their location within specific metropolitan statistical areas. In keeping with the measurement of other variables, monthly unemployment rates were collected over the course of the fiscal year and the mean across all months was taken to form an annual average.

Unit age. Unit age was measured as the number of years since a given establishment's opening date and was included as it may have effects on other variables of interest. Specifically, older establishments may have higher-tenured workforces thus affecting tenure-diversity relationships. In addition, older establishments may have older, more loyal, and better established customer bases which may drive gross sales.

Analytical Strategy and Rationale

General rationale. In order to investigate the aforementioned hypotheses, hierarchical multiple regression (HMR) analysis employing ordinary least squares (OLS) techniques was utilized. This methodology is well-suited to the current investigation for two key reasons. First, such a technique allows the effects of theoretically precedent variables to be partialed out of the observed variance in performance before the effects of predictors assumed to operate later in a presumed causal chain are considered and thus, allows for an analysis that "reflects their presumed causal priority" (Cohen et al., 2003: 158). Such an ordering allows for arguably stronger tests of the proposed hypotheses as later steps in the analyses—which reflect the addition of the study's focal variables—must explain variance above and beyond the effects of variables added in previous steps.

Second, and pertaining specifically to hypotheses proposing interactive effects of productive capacity with diversity and collective size respectively, utilizing HMR allows for simple computation of the squared semi-partial correlation for the product term, which is the standardized indicator of the amount of unique variance accounted for by the interaction effect—i.e., variance that is accounted for over and above the "main effects" of its component terms.[8] Specifically, while the coefficient associated with the interaction term provides evidence of the form of the proposed interaction and its associated *t*-test and resulting *p*-value indicate statistical significance, the coefficient itself does not indicate the standardized strength of the interaction. By employing HMR, such a value may be calculated based on the difference between multiple squared correlations (R^2) across main-effects-only and interaction models. In particular, the main-effects-only model exists in the form:

$$Y = \alpha + \beta_1 X + \beta_2 Z + \varepsilon$$

[8] "Main effects" is used here to refer to the component effects of the interaction term in the interactive specification. However, the coefficients associated with such "main effects" are actually conditional on one component being equal to zero. For instance, in an equation of the form $Y = \alpha + \beta_1 X + \beta_2 Z + \beta_3 XZ + \varepsilon$, where *X* and *Z* represent focal variables under consideration, β_1 refers to the effect of *X* on Y when $Z = 0$ and β_2 refers to the effect of *Z* on *Y* when $X = 0$. Thus, these coefficients do not reflect main effects *per se* (as they do in a purely main-effects specification of the form $Y = \alpha + \beta_1 X + \beta_2 Z + \varepsilon$) but rather indicate simple conditional effects (Jaccard & Turrisi, 2003).

where Y is the criterion value, α is the intercept, X and Z represent the variables of interest, and ε represents the error term. In contrast, the interaction-effects model adds a product term to the above equation such that:

$$Y = \alpha + \beta_1 X + \beta_2 Z + \beta_3 XZ + \varepsilon.$$

When each respective model is assessed it yields an R^2 value based on variance explained in the data being analyzed. If a statistically significant interaction is present, then the difference in the R^2 values should be statistically significant according to an hierarchical omnibus F-test.[9] Notably, while this test yields the same information as the significance value associated with the coefficient (β_3) of the product term, the difference that feeds into the F-test indicates the standardized effect size of the interaction itself. For instance, if the main-effects-only specification yields a squared multiple correlation of .64 and the interaction model with the product term yields a value of .67, the difference of .03 indicates that the interaction effect explains 3% of the total variance in the criterion (Jaccard & Turrisi, 2003). Given these benefits, HMR thus presents a viable analytical framework to analyze the hypotheses proposed by this study.

Addressing OLS assumptions. As with all statistical methodologies, OLS is reliant upon a set of assumptions that inform its appropriateness for a given dataset. Among the assumptions inherent in OLS analyses is the correct specification of the relationship between independent and dependent variables. Specifically, and most pertinent to the current case, misspecification of a relationship as linear when it, in fact, is curvilinear or quadratic may distort coefficients and

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[9] $F = \frac{(R_2^2 - R_1^2)/(k_2 - k_1)}{(1 - R_2^2)/(N - k_2 - 1)}$ where R_2 is the multiple R for the expanded equation, R_1 is the multiple R for the original equation, k_2 is the number of predictors in the expanded equation, k_1 is the number of predictors in the original equation, and N is the total sample size (Jaccard & Turrisi, 2003: 12).

standard errors as well as significance tests and confidence intervals (Cohen et al., 2003). While such concerns are generally not overly pressing in the absence of theoretical reasoning to suggest their presence, one variable under consideration in the current study, collective size, has been argued to exhibit a curvilinear relationship with performance criteria (Nieva et al., 1985). Thus, this variable in particular, and all other variables more broadly, were examined to assess the linearity of their respective relationships with both outcome variables (customer satisfaction and gross sales) via scatterplots that graphed all combinations of independent variables with dependent variables. Visual analysis of these plots revealed linear relationships in all cases.

An additional assumption of OLS methodologies is that no measurement error exists in the independent variables; in practice, however, this assumption is seldom, if ever, satisfied. As mentioned previously, at least some variables considered have near-perfect reliability (i.e., demographic indicators such as age, race/ethnicity, and gender; Cohen et al., 2003). Further, other focal variables—collective size, tenure diversity, subgroup occupation, and unit age—appear unlikely to be subject to extensive measurement error. Notably some error may be present in measures of unemployment rate and, potentially, productive capacity. Potential unreliability in these variables should attenuate observed relationships thus resulting in more conservative estimates of their effects to the extent that unreliability is indeed present. A third assumption of OLS is that of homoscedasticity or that "the variance of the residuals around the regression line is constant regardless of the value of *X*" (Cohen et al., 2003: 120). Failure to satisfy this assumption may bias standard errors and thus, tests of statistical significance, but does not pose a major threat to analytical results unless "the ratio of conditional variances at different values of *X* exceeds 10" (ibid.). Nonetheless, the assumption of homoscedasticity was tested via visual inspection of plots of residuals against predicted values. In no case was a "large" degree of heteroscedasticity observed.

Characteristics of the current sample preclude many concerns surrounding two other assumptions of OLS, namely the independence and normality of residuals, respectively. In the former case, independence of residuals is assured by random selection. With respect to nonnormality of residuals, Cohen et al. (2003: 120) state, "In large samples, nonnormality of the residuals does not lead to serious problems with the interpretation of either significance tests or confidence intervals." Given the sample size in the current work, then, nonnormality of residuals does not appear to be a significant concern. Nonetheless, potential nonnormality was assessed using normal probability plots and histograms of residuals; in no cases was nonnormality of residuals observed.

Analyses

Following the suggestion of Jaccard and Torrisi (2003: 65) analyses were generated in hierarchically well-formulated models, "in which all lower-order components of the highest-order interaction term are included in the model." Specifically, variables were entered into the analysis in three steps. In Step 1, control variables were entered. In Step 2, dependent upon the hypothesis under investigation, focal variables (productive capacity, collective size, age diversity, tenure diversity, ethnic diversity, and/or gender diversity) were entered. Finally, in Step 3, interaction terms were entered. All interaction terms and independent variables were mean-centered to eliminate non-essential multicollinearity and to improve the interpretability of results (Cohen et al., 2003).

CHAPTER 5

RESULTS

Descriptive Statistics

Table 1 reports the means, standard deviations, and zero-order Pearson correlations for all study variables. Productive capacity positively and significantly correlated with collective performance in the form of customer satisfaction (r = .15, p < .01), gross sales (r = .26, p < .01), and gross sales per customer (r = .17, p < .01), suggesting initial support for *Hypothesis 1*. Also of note, the included control variables shared significant correlations with collective performance outcomes. Specifically, MSA population correlated with customer satisfaction (-.18, p < .01), gross sales (r = .28, p < .01), and gross sales per customer (r = .54, p < .01) while unemployment rate significantly correlated with gross sales per customer (r = .19, p < .01). As a unit-level control, unit age correlated significantly with both gross sales (r = .29, p < .01) and gross sales per customer (r =.-.16, p < .01). Finally, and somewhat surprisingly, negative and significant correlations between customer satisfaction and gross sales (r = -.20, p < .01) and gross sales per customer (r = -.19, p < .01) were revealed.

Hypothesis Tests

Table 2 contains the results of the hierarchical regression analyses testing for the main effect of productive capacity on customer satisfaction, gross sales, and gross sales per customer, respectively. For both customer satisfaction (b = .13; β = .21; p < .01) and gross sales (b = 278905; β = .21; p < .01), the relationship with productive capacity was positive and significant.

TABLE 1
Means, Standard Deviations, and Pearson Correlations[a]

	Variable	Mean	s.d.	1	2	3	4	5	6	7	8	9	10	11
1.	Unemployment Rate	9.11	2.11											
2.	MSA Population	3081034.90	4080646.46	.08										
3.	Unit Age	23.90	9.83	-.01	-.06									
4.	Productive Capacity	0.83	0.06	.20**	.18**	.06								
5.	Unit Size	83.49	13.92	.02	.08	.33**	.21**							
6.	Age Diversity	11.22	1.49	.14**	-.01	.41**	.26**	.06						
7.	Tenure Diversity	71.95	18.04	.06	-.03	.72**	.22**	.25**	.61**					
8.	Ethnic Diversity	0.48	0.15	.12*	.37**	.04	-.01	.06	-.01	.03				
9.	Gender Diversity	0.49	0.02	-.05	.06	.06	.03	.12*	.04	.06	.13**			
10.	Customer Sat.	0.60	0.04	-.02	-.18**	-.09	.15**	-.05	.03	-.04	-.34**	-.08		
11.	Gross Sales	309391.64	75508.17	-.00	.28**	.29**	.26**	.84**	.05	.23**	.20**	.14**	-.20**	
12.	Gross per Customer	20.52	1.76	.19**	.54**	-.16**	.17**	.09	-.09	-.16**	.28**	-.07	-.19**	.37**

[a] $N = 400$ (units).

* $p < .05$

** $p < .01$

TABLE 2

Results of Hierarchical Regression Analyses for Hypothesis 1: Productive Capacity Main Effects[a]

	Customer Satisfaction		Gross Sales		Gross Sales per Customer	
Independent Variables	**Model 1**	**Model 2**	**Model 3**	**Model 4**	**Model 5**	**Model 6**
Step 1: Controls						
Unemployment Rate	-.01	-.05	-.02	-.06	.15**	.13**
MSA Population	-.18**	-.22**	.31**	.27**	.52**	.51**
Unit Age	-.10*	-.11*	.31**	.30**	-.13**	-.13**
Step 2: Predictors						
Productive Capacity		.21**		.21**		.06
Unit Size						
Age Diversity						
Tenure Diversity						
Ethnic Diversity						
Gender Diversity						
Step 3: Interaction Terms						
Capacity × Unit Size						
Capacity × Age Diversity						
Capacity × Tenure Diversity						
Capacity × Ethnic Diversity						
Capacity × Gender Diversity						
R^2	.04	.08	.18	.22	.33	.33
Adjusted R^2	.03	.07	.17	.21	.32	.32
ΔR^2	.04	.04	.18	.04	-	.00
ΔF	5.64**	16.81**	28.18**	20.82**	63.83**	2.18

[a] Standardized coefficients are reported; *N* = 400 units; † $p < .10$; * $p < .05$; ** $p < .01$

TABLE 3

Results of Hierarchical Regression Analyses for Hypothesis 2: Size x Capacity Interactions[a]

	Customer Satisfaction		Gross Sales		Gross Sales per Customer	
Independent Variables	**Model 7**	**Model 8**	**Model 9**	**Model 10**	**Model 11**	**Model 12**
Step 1: Controls						
Unemployment Rate	-.05	-.05	-.04†	-.05†	.14**	.14**
MSA Population	-.21**	-.21**	.22**	.22**	.50**	.50**
Unit Age	-.10†	-.10†	.03	.04	-.16**	-.17**
Step 2: Predictors						
Productive Capacity	.21**	.22**	.06*	.06*	.05	.04
Unit Size	-.05	-.05	.80**	.80**	.09*	.10
Age Diversity						
Tenure Diversity						
Ethnic Diversity						
Gender Diversity						
Step 3: Interaction Terms						
Capacity × Unit Size		.02		.02		-.02
Capacity × Age Diversity						
Capacity × Tenure Diversity						
Capacity × Ethnic Diversity						
Capacity × Gender Diversity						
R^2	.08	.08	.76	.76	.34	.34
Adjusted R^2	.07	.07	.76	.75	.33	.34
ΔR^2	-	.000	-	.000	-	.000
ΔF	7.04**	.20	246.39**	.39	40.04**	.29

[a] Standardized coefficients are reported; *N* = 400 units; † *p* < .10; * *p* < .05; ** *p* < .01

While the relationship between capacity and gross sales per customer (b = 1.95; β = .06; p = .14) was in the predicted direction, it failed to reach statistical significance. Taken together, these findings provide moderate support for *Hypothesis 1*.

Hypothesis 2 predicted that the positive relationship between capacity and performance would be stronger in larger, versus smaller, collectives or units. As depicted in *Table* 3, while capacity predicted both customer satisfaction (b =.14; β = .22; p < .01) and gross sales (b =84017; β = .06; p < .05), its relationship with gross sales per customer, while in the predicted direction, failed to reach statistical significance (b =1.23; β = .04; NS). Unit size emerged as a significant predictor of gross sales (b =4322; β = .80; p < .01) and gross sales per customer (b =.01; β = .10; p < .05), but did not significantly predict customer satisfaction (b =.00; β = -.05; NS). The interactions between productive capacity and unit size in predicting customer satisfaction (b =.00; β = .02; NS), gross sales (b =1494; β = .02; NS), and gross sales per customer (b = -.05; β = -.02; NS) failed to reach statistical significance in all tested models. Thus, no support was found for *Hypothesis 2*.

Table 4 presents the results of hierarchical regressions pertaining to *Hypothesis 3a*, which predicted that within-unit age diversity would moderate the positive relationship between capacity and performance such that the relationship would be stronger in units with greater, versus lesser, age diversity. As before, capacity emerged as a significant predictor of customer satisfaction (b =.13; β = .20; p < .01) and gross sales (b =317652; β = .24; p < .01), but was also a marginally significant predictor of gross sales per customer when age diversity was included as a predictor (b =2.48; β = .08; p = .07; *see Model 18*). While age diversity did not significantly predict customer satisfaction (b =.00; β = .04; NS), it negatively and significantly predicted both gross sales (b =-7547; β = -.15; p < .01) and gross sales per customer (b = -.11; β = -.09; p < .05).

Finally, the interaction between capacity and age diversity was not significant as a predictor of customer satisfaction (*b* =.01; β = .04; NS), gross sales (*b* = -24308; β = -.03; NS), nor gross sales per customer (*b* = -.51; β = -.03; NS). Thus, no support was found for *Hypothesis 3a*.

The results of regressions pertaining to *Hypothesis 3b*, which proposed a positive interaction between capacity and tenure diversity as predictors of collective performance, are presented in *Table 5*. With tenure diversity included as a predictor of performance, capacity emerged as a significant predictor of customer satisfaction (*b* =.135; β = 21; $p < .01$) and gross sales (*b* =295612; β = .22; $p <$ 01), and notably, also significantly predicted gross sales per customer (*b* = 2.74; β = .09; $p < .05$). Tenure diversity did not exhibit a significant main effect on customer satisfaction (*b* = .00; β = -.02; NS) or gross sales (*b* = -210; β = -.05; NS), but did significantly and negatively predict gross sales per customer (*b* = -.02; β = -.17; $p < .01$). The interaction between capacity and tenure diversity did not reach statistical significance for models predicting customer satisfaction (*b* =.00; β = 00; NS), gross sales (*b* =2348; β = .04; NS), or gross sales per customer (*b* = -.07; β = -.05; NS) and therefore, *Hypothesis 3b* is not supported.

Table 6 presents the results the of analyses pertaining to *Hypothesis 3c*, which predicted that unit ethnic diversity would moderate the positive relationship between capacity and performance such that capacity would be a stronger predictor of performance in more heterogeneous, versus less heterogeneous, units. Capacity emerged as significant predictor of both customer satisfaction (*b* = .12; β = .18; $p < .01$) and gross sales (*b* = 291089; β = .22; $p < .01$) but failed to exhibit a statistically significant main effect as a predictor of gross sales per guest (*b* = 1.75; β = .06; NS), although the effect was in the predicted direction. The main effects of ethnic diversity on collective performance were mixed with ethnic diversity exhibiting a significant and negative relationship with customer satisfaction (*b* = -.07; β = -.30; $p < .01$) and

TABLE 4

Results of Hierarchical Regression Analyses for Hypothesis 3a: Capacity x Age Diversity Interactions[a]

	Customer Satisfaction		Gross Sales		Gross Sales per Customer	
Independent Variables	**Model 13**	**Model 14**	**Model 15**	**Model 16**	**Model 17**	**Model 18**
Step 1: Controls						
Unemployment Rate	-.05	-.05	-.05	-.05	.14**	.14**
MSA Population	-.22**	-.21**	.27**	.26**	.51**	.50**
Unit Age	-.13*	-.12*	.35	.35**	-.10*	-.10*
Step 2: Predictors						
Productive Capacity	.20**	.20**	.24**	.24**	.08†	.08†
Unit Size						
Age Diversity	.04	.04	-.15**	-.15**	-.09*	-.09*
Tenure Diversity						
Ethnic Diversity						
Gender Diversity						
Step 3: Interaction Terms						
Capacity × Unit Size						
Capacity × Age Diversity		.04		-.03		-.03
Capacity × Tenure Diversity						
Capacity × Ethnic Diversity						
Capacity × Gender Diversity						
R^2	.08	.08	.23	.24	.34	.34
Adjusted R^2	.07	.07	.23	.22	.33	.33
ΔR^2	-	.00	-	.00	-	.00
ΔF	6.96**	0.58	24.10**	0.48	39.93**	.44

[a] Standardized coefficients are reported; *N* = 400 units; † *p* < .10; * *p* < .05; ** *p* < .01

TABLE 5

Results of Hierarchical Regression Analyses for Hypothesis 3b: Capacity x Tenure Diversity Interactions[a]

	Customer Satisfaction		Gross Sales		Gross Sales per Customer	
Independent Variables	**Model 19**	**Model 20**	**Model 21**	**Model22**	**Model 23**	**Model 24**
Step 1: Controls						
Unemployment Rate	-.05	-.05	-.06	-.06	.14**	.14**
MSA Population	-.22**	-.22**	.27**	.27**	.51**	.50**
Unit Age	-.10	-.09	.33**	.34**	-.01	-.02
Step 2: Predictors						
Productive Capacity	.21**	.21**	.22**	.22**	.09*	.09*
Unit Size						
Age Diversity						
Tenure Diversity	-.02	-.02	-.05	-.05	-.17**	-.17**
Ethnic Diversity						
Gender Diversity						
Step 3: Interaction Terms						
Capacity × Unit Size						
Capacity × Age Diversity						
Capacity × Tenure Diversity		.00		.04		-.05
Capacity × Ethnic Diversity						
Capacity × Gender Diversity						
R^2	.08	.08	.22	.22	.34	.35
Adjusted R^2	.07	.07	.21	.21	.33	.34
ΔR^2	-	.00	-	.00	-	.00
ΔF	6.88**	.00	22.00**	.61	41.08**	.28

[a] Standardized coefficients are reported; *N* = 400 units; † $p < .10$; * $p < .05$; ** $p < .01$

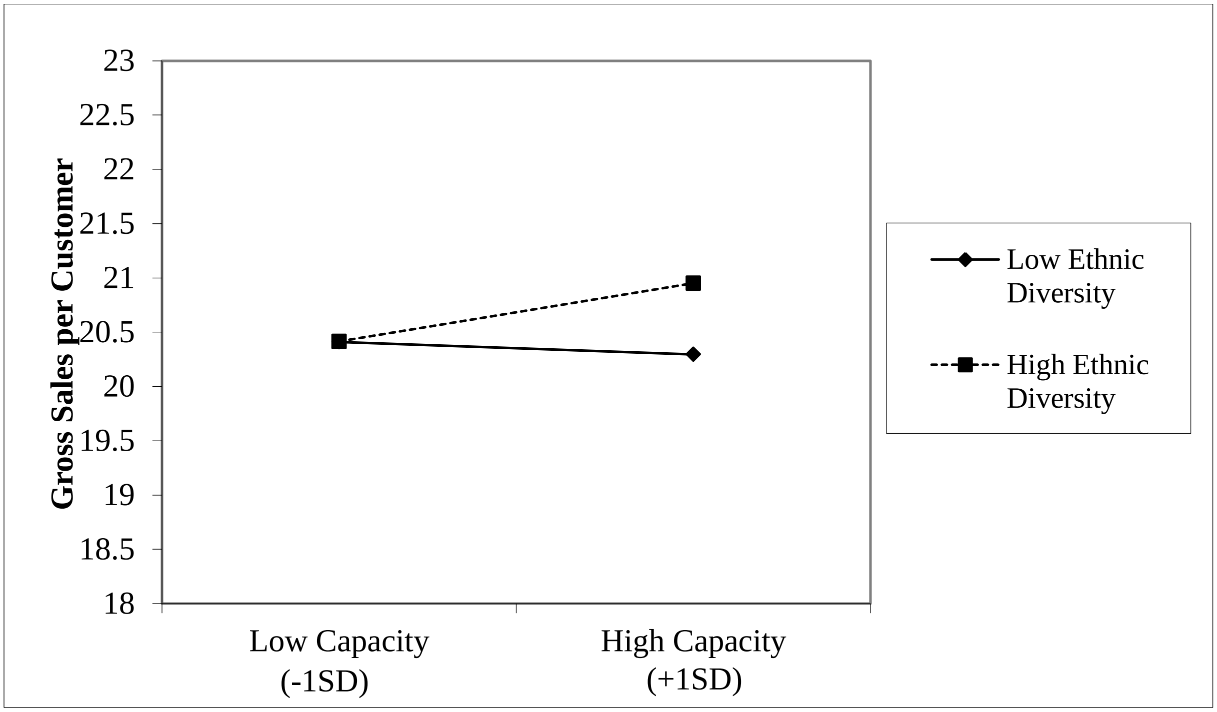
TABLE 6

Results of Hierarchical Regression Analyses for Hypothesis 3c: Capacity x Ethnic Diversity Interactions[a]

	Customer Satisfaction		Gross Sales		Gross Sales per Customer	
Independent Variables	**Model 25**	**Model 26**	**Model 27**	**Model 28**	**Model 29**	**Model 30**
Step 1: Controls						
Unemployment Rate	-.02	-.02	-.07	-.07	.12**	.12**
MSA Population	-.10*	-.10*	.22**	.22**	.47**	.47**
Unit Age	-.09†	-.09†	.29**	.29**	-.14**	-.14**
Step 2: Predictors						
Productive Capacity	.17**	.18**	.22**	.22**	.07†	.06
Unit Size						
Age Diversity						
Tenure Diversity						
Ethnic Diversity	-.30**	-.30**	.12*	.12*	.10*	.10*
Gender Diversity						
Step 3: Interaction Terms						
Capacity × Unit Size						
Capacity × Age Diversity						
Capacity × Tenure Diversity						
Capacity × Ethnic Diversity		-.05		.02		.08*
Capacity × Gender Diversity						
R^2	.16	.16	.23	.23	.34	.34
Adjusted R^2	.14	.15	.22	.22	.33	.33
ΔR^2	-	.00	-	.000	-	.01
ΔF	14.46**	.28	23.45**	.15	40.19**	3.86*

[a] Standardized coefficients are reported; N = 400 units; † p < .10; * p < .05; ** p < .01

FIGURE 7
Effect of the Interaction of Productive Capacity and Ethnic Diversity on Gross Sales per Customer



positive and significant relationships with gross sales (b = 58966; β = .12; $p < .01$) and gross sales per customer (b = 1.10; β = .10; $p < .05$).

The capacity-ethnic-diversity interaction was not significant as a predictor of customer satisfaction (b = -.24; β = -.051; NS) or gross sales (b = 163258; β = .02; NS), but did emerge as significant, and in the predicted direction, in the model predicting gross sales per guest (b = 18.09; β = .08; p = .05; *see Model 30*). *Figure 7* plots the interaction effect by showing the slopes of regression lines under conditions of low and high ethnic diversity. Subsequent analysis of simple slopes (Dawson, 2014) revealed that, while capacity did not share a significant relationship with gross sales per customer in units with low ethnic diversity (b = -.96; β = -.08; NS), capacity did significantly and positively predict gross sales per guest in units with high

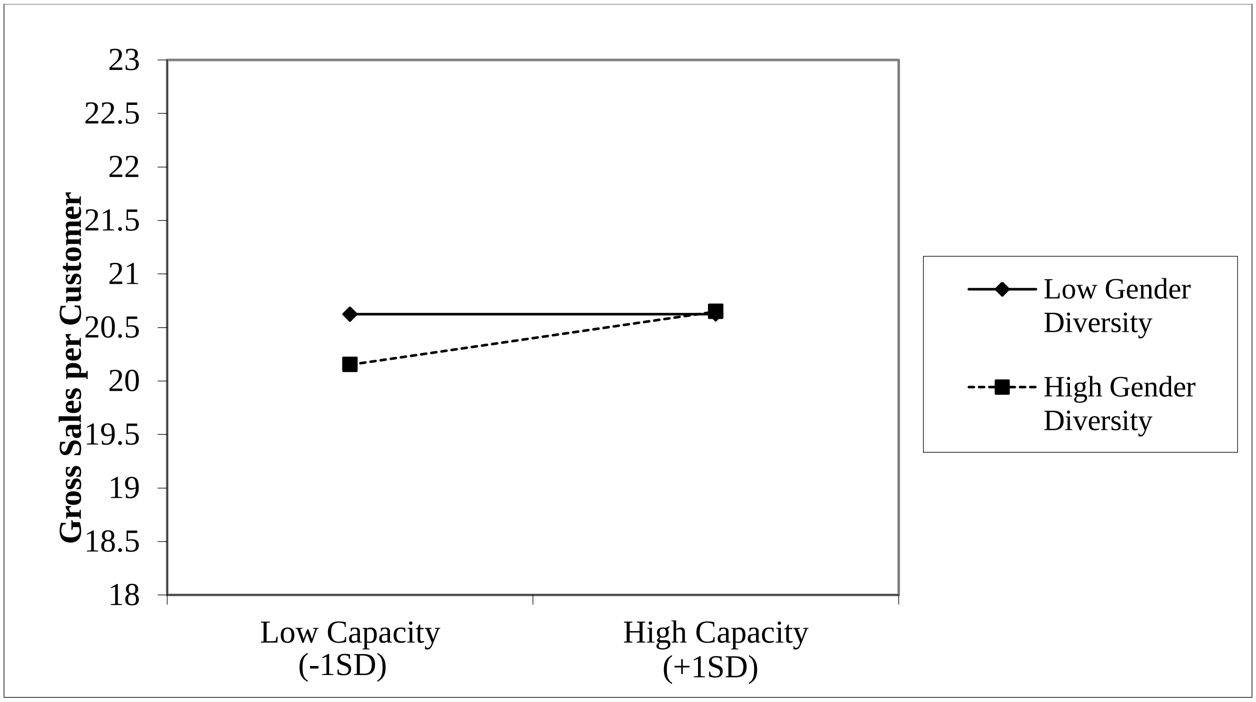
TABLE 7

Results of Hierarchical Regression Analyses for Hypothesis 3d: Capacity x Gender Diversity Interactions[a]

	Customer Satisfaction		Gross Sales		Gross Sales per Customer	
Independent Variables	**Model 31**	**Model 32**	**Model 33**	**Model 34**	**Model 35**	**Model 36**
Step 1: Controls						
Unemployment Rate	-.05	-.05	-.06	-.06	.13**	.13**
MSA Population	-.21**	-.21**	.26**	.26**	.51**	.51**
Unit Age	-.11*	-.11*	.29**	.29**	-.13**	-.13**
Step 2: Predictors						
Productive Capacity	.21**	.21**	.21**	.21**	.07	.07
Unit Size						
Age Diversity						
Tenure Diversity						
Ethnic Diversity						
Gender Diversity	-.07	-.08	.10*	.11*	-.09*	-.06
Step 3: Interaction Terms						
Capacity × Unit Size						
Capacity × Age Diversity						
Capacity × Tenure Diversity						
Capacity × Ethnic Diversity						
Capacity × Gender Diversity		-.02		.05		.07†
R^2	.09	.09	.23	.23	.34	.34
Adjusted R^2	.07	.07	.22	.22	.33	.33
ΔR^2	-	.000	-	.00	-	.00
ΔF	7.35**	.15	23.02**	.92	40.05**	2.67†

[a] Standardized coefficients are reported; *N* = 400 units; † *p* < .10; * *p* < .05; ** *p* < .01

FIGURE 8
Effect of the Interaction of Productive Capacity and Gender Diversity on Gross Sales per Customer



ethnic diversity (b = 4.47; β = .38; p < .01). Taken together, the results of the regression and simple slopes analyses suggest marginal support for *Hypothesis 3c*, namely that the capacity-performance relationship is stronger under conditions of high ethnic diversity.

Hypothesis 3d predicted that capacity would exhibit stronger effects on performance in units with greater, rather than lesser, gender diversity. Results of regression analyses pertaining to this hypothesis are presented in *Table 7*. Capacity exhibited a significant and positive main effect as a predictor of customer satisfaction (b = .13; β = .21; p < .01) and gross sales (b = 276569; β = .21; p < .01), but did not reach statistical significance as a predictor of gross sales per guest (b = 2.08; β = .07; NS). Gender diversity's main effects on collective performance were mixed, with a negative and non-significant relationship observed between gender diversity and both customer satisfaction (b = -.15; β = -.08; NS) and gross sales per guest (b = -5.580; β = -.06;

NS). As a predictor of gross sales, however, gender diversity exhibited a positive and significant relationship (b = 414641; β = .11; p < .05).

While the proposed interaction effect between capacity and gender diversity significantly predicted neither customer satisfaction (b = -.61; β = -.02; NS) nor gross sales (b = 2786673; β = .05; NS), it did emerge as a marginally significant predictor of gross sales per customer (b = 102.58; β = .07; p = .10). *Figure 8* illustrates the effect of the interaction between productive capacity and gender diversity on gross sales per customer. Simple slopes analysis revealed that, while capacity was not a significant predictor of performance in relatively gender-homogenous groups (b = .02; β = .00; NS), the capacity-performance relationship was in the predicted direction and attained statistical significance for units with a high degree of gender heterogeneity (b = 4.13; β = .05; p < .01), thus providing marginal support for *Hypothesis 3d*.

CHAPTER 6

DISCUSSION

This study sought to examine two core propositions. The first was that, as a collective resource, productive capacity should positively predict collective performance. The logic underlying this proposition is straightforward. On the one hand, stable membership can contribute to the growth and maintenance of collective capabilities, for instance through enhancements to coordination, knowledge sharing, expertise recognition, shared mental model development, and the like (Harris et al., 2012). On the other hand, changing membership can lead to the breakdown of such capabilities through process losses encompassing non-germane task focus, redundant effort, and illogical organization (Steiner, 1972; McGrath, 1991; Summers et al., 2012). It was argued that, if both "growth" and "breakdown" dynamics generate collective performance effects, a theoretical approach that considered (and further, measured) accumulation and degradation dynamics simultaneously and over time, would also be predictive of performance.

With respect to this proposition, the overall supporting evidence was moderate to strong. Productive capacity consistently predicted performance in terms of customer satisfaction and gross sales. Specifically, capacity emerged as a significant predictor of customer satisfaction (β = .17 - .22) in every model specification where it was included and the magnitudes of observed capacity-customer-satisfaction relationships remained relatively stable regardless of the other predictors included in a given model. Capacity was also a significant and consistent predictor of gross sales (β = .06 - .24), although this relationship proved to be sensitive to which unit-level characteristics were modeled alongside it (e.g., models that included unit size as a predictor of gross sales exhibited the lowest capacity-performance magnitudes and ranged from β = .06 - .07; *see Models 9*, *10*, *39*, and *40*). Nonetheless, in 9 out of 13 models predicting gross sales, the magnitude of capacity-performance relationships exceeded β = .20.

Relationships of capacity to gross sales per customer were less consistent and of smaller magnitude across all model specifications, perhaps due to the relatively large influence of variables reflecting local economic and demographic conditions. For instance, while MSA population shared a moderate correlation with gross sales (r = .28; p < .01), the correlation of population with gross sales per customer was nearly twice that magnitude (r = 54; p < .01). Additionally, and somewhat unexpectedly, the local unemployment rate also correlated significantly and positively with gross sales per guest (r = .19; p < .01), although it shared no significant correlation with gross sales (r = .00; NS). While initially a counterintuitive finding, this positive correlation makes more sense when the mean value of gross sales per customer, $20.52, is taken into account. As unemployment rate rises, it appears likely that the lowest-spending segment of a given establishment's customer base is removed (i.e., the "bottom of the pyramid" drops off or the pyramid is truncated), driving sales per customer upwards even in the face of no statistically discernible effect on gross sales.[10]

Regardless of the explanation behind this observed relationship, the fact remains that the level of gross sales per customer is largely predicated on local demographic and economic conditions, a fact that is borne out by the consistent and relatively sizable beta-weights that MSA

[10] An alternative explanation of this relationship is that the product/service combination offered by the focal organization is, economically, an inferior good. Increasing unemployment levels could portend decreasing local average income and this decrease in income may increase demand for, and following this, sales of the product/service combination in question. Given gross sales per customer's estimated mean value of $20.52 (and its value three standard deviations below the mean of $15.24), ample, and less costly, substitutes for this product/service combination most likely abound. Combined with the lack of relationship between unadjusted gross sales and the local unemployment rate, the "inferior good explanation" of this effect may be dismissed in favor of the "truncated pyramid" explanation.

population (β = .46 - .52) and local unemployment rate (β = .12 - .15) contribute to the prediction of gross sales per guest across all tested models. Further, these two predictors alone account for roughly 31% of the variance (F = 88.83; p < .01) in gross sales per guest (as opposed to 3% of the variance in customer satisfaction and 8% of the variance in gross sales). Given these strong location-based influences on individual spending behavior in the focal units, models examining gross sales per guest as a dependent variable may represent the most conservative tests of the proposed main effects hypothesis (i.e., *Hypothesis 1*). As *Table* 8 shows, productive capacity emerges as a significant predictor of customer satisfaction (b = .12; β = .18; p < .01) and gross sales (b = 96255; β = .07; p < .01) as well gross sales per guest (b = 2.84; β = .09; p < .05; *see Model 41*) even when the effects of unit characteristics—i.e., unit size, age diversity, tenure diversity, ethnic diversity, and gender diversity—are controlled

Taken together, these results suggest that productive capacity does indeed predict various forms of collective performance, and further, does so over and above the (potentially strong) effects of external location and unit characteristics. This study is among the first empirical tests of the theoretical propositions advanced by Hausknecht & Holwerda's (2013) capacity-based perspective, which suggests that, in addition to the movement of employees into and out of collectives, the accumulated individual proficiencies of leavers, stayers, and newcomers, as well as the patterns and timing of their departures, matter with regard to collective performance. These findings lend initial empirical support to that perspective and, in so doing, point to its future viability as a theoretical lens through which to view the accumulation and degradation of collective resources borne of human interaction and cooperation. Concordantly, these findings also provide initial support for Hausknecht and Holwerda's (2013) operationalization of capacity, although further refinement appears to be in order (discussed later).

TABLE 8

Results of Hierarchical Regression Analyses for Full Models[a]

Variables	Customer Satisfaction		Gross Sales		Gross Sales per Guest	
	Model 37	Model 38	Model 39	Model 40	Model 41	Model 42
Step 1: Controls						
Unemployment Rate	-.02	-.03	-.05	-.05	.13**	.13**
MSA Population	-.10*	-.10†	.18**	.19**	.46**	.46**
Unit Age	-.06	-.05	.03	.03	-.05	-.08
Step 2: Predictors						
Productive Capacity	.18**	.20**	.07**	.07*	.09*	.06
Unit Size	-.03	-.03	.79**	.79**	.09*	.10*
Age Diversity	.04	.03	-.03	-.02	-.02	-.01
Tenure Diversity	-.05	-.05	.02	.01	-.15*	-.14*
Ethnic Diversity	-.29**	-.29**	.09**	.09**	.11*	.10*
Gender Diversity	-.04	-.03	.01	.02	-.11*	-.10*
Step 3: Interaction Terms						
Capacity × Unit Size		.04		.00		-.02
Capacity × Age Diversity		.04		-.02		-.01
Capacity × Tenure Diversity		-.03		.04		-.05
Capacity × Ethnic Diversity		-.05		.01		.07†
Capacity × Gender Diversity		.00		.02		.05
R^2	.16	.16	.77	.77	.37	.38
Adjusted R^2	.14	.13	.76	.76	.35	.36
ΔR^2	.08	.00	.01	.00	.03	.01
ΔF	8.89**	.38	3.12**	.46	4.8**	1.21

[a] Standardized coefficients are reported; N = 400 units; † $p < .10$; * $p < .05$; ** $p < .01$

The second core proposition of the study was that the capacity-performance relationship would be affected by the extant level of complexity in the work environment, with more complex environments subject to stronger capacity-performance linkages than less complex environments. Specifically, increases in unit size and unit demographic diversity were proposed to correspond to increases in member coordination complexity, or the added complexity affecting a given task based on the social configuration of those who collectively perform it (Espinosa et al., 2007). When levels of this “added” complexity are high, demands for sophisticated and precise collective processes are high as well (Saavedra et al., 1993; Kozlowski & Bell, 2002). Given that productive capacity encompasses such sophisticated and precise collective processes, capacity should be more central to, and thus share a stronger relationship with, performance under such conditions.

Evidence supporting this proposition was found in only two instances—for interaction effects between capacity and ethnic diversity and gender diversity, respectively—both predicting gross sales per customer. The emergence of these effects as significant and in the predicted direction is encouraging and lends some support to a small body of work that contends collective resources are more important to performance in complex environments (Gully et al., 1995; Gully et al., 2002; Espinosa et al., 2007; LePine et al., 2008). While, on the whole, support for this second proposition and its accordant hypotheses was meager, both theoretical and methodological factors may be at play that help to explain this pattern of (non-) findings.

As mentioned previously, no support was found for *Hypothesis 2*, which predicted a capacity-by-size interaction that would significantly affect performance outcomes. The emergence of such an interaction may be predicated upon the level of task-environment complexity—sequencing, interdependence, and integration—inherent in the work. This form of complexity was constant in the current sample, while member coordination complexity was theorized to vary positively with size. Recalling the work of Van de Ven and colleagues (1976), task-environment complexity falls along a continuum from pooled interdependence at one end, where collective performance is the sum of individual efforts with relatively little interaction between individuals, to reciprocal interdependence, where collective performance more closely resembles a multiplicative function of such efforts.

If task-environment complexity in the current sample approximated a pooled mode of interaction, larger unit size may not have necessitated higher member coordination complexity. Rather, a larger unit size may have simply meant that the "sum" of collective performance was taken over a larger number of employees and further, no additional demands were placed on the work unit in terms of the communication, cooperation, and collaboration necessary for the successful completion of work. In the face of this potential lack of additional functional demands, which appears possible given the relative standardization of operational procedures in the current organization, capacity would be no more valuable to a larger work unit than to its smaller counterparts.

Hypotheses 3a-3d predicted interactions between capacity and various surface-level demographic characteristics—age, tenure, ethnicity, and gender—such that capacity-performance relationships would be stronger in more demographically diverse work units. These interactions were found only when gross sales per guest was predicted and only for ethnic and gender diversity, suggesting a confluence of methodological and theoretical factors that influenced the overall pattern of results. With respect to methodological factors, gross sales per guest may have been the "least noisy" of the performance outcomes examined and this may have allowed for the emergence of statistically significant interaction effects. Specifically, while the relatively strong relationships between gross sales per guest and both the local unemployment rate and MSA population left less variance to be explained by focal (i.e., theorized) predictors, models predicting gross sales per customer may have accounted more completely for the influence of unobserved covariates relative to those models predicting customer satisfaction and gross sales.

On the theoretical side, it is somewhat unsurprising that the capacity-diversity interactions that emerged did so for ethnic and gender diversity and not for age and tenure diversity. More specifically, meaningful differences in the visibility of such characteristics may have played a role in the observed pattern of findings. Given the higher visibility of gender and ethnic characteristics—differences which may be perceived more readily than age or tenure—diversity pertaining to these dimensions appears more likely to generate the member coordination complexity that would drive a capacity-by-diversity interaction. More specifically, and following social identity and social categorization theories, gender and ethnicity provide a more easily discerned and firmer basis to establish one's own (as well as surrounding others') membership in a given social category. For instance, it is (more or less) immediately apparent whether a co-worker is male or female, which allows similarly immediate designation of that co-worker as belonging to an in-group or an out-group, relative to the observer. By contrast, a characteristic such as tenure is not only less immediately visible—one cannot generally deduce the tenure of a co-worker via visual inspection—but, the boundaries of what constitutes the in-group or out-group are also less clear relative to gender or ethnicity.

For example, while the boundaries of gender-based social categories are clear (male versus female), they are far less so for a characteristic like tenure, where a social category or cohort could just as easily be defined as existing of those employees with 3 to 5 years of tenure as it could be defined as existing of those with 4 to 7 years of tenure or any other range. Further, the definition of these boundaries and their resulting in-group/out-group designations is more likely to vary by observer than gender- or ethnicity-based boundaries. Thus, while the in- or out-group status of another may be designated consistently at the level of the individual observer based on characteristics such as age or tenure, such designations likely become equivocal across multiple observers. The resulting "loose" unit-level definition of an age- or tenure-based in-group/out-group may mitigate the operation of social categorization effects, thus placing no further demands on the unit in terms of the sophistication and precision necessary to collectively accomplish tasks, and preclude a positive interaction effect between capacity and age- or tenure-based diversity in predicting collective performance.

Combined with these differences in the visibility and consistency of in-group/out-group distinctions, are differences in the salience—or "social significance" (Reagans, 2013: 193)—of various demographic characteristics. For instance, while age or tenure may have functional- or task-based connotations among employees, ethnicity and gender "in addition to their relevance for tasks (e.g., product design, marketing, sales, service delivery) also relate to personal identity and powerful social, political, and historical forces" (Alderfer & Sims, 2003: 607). Thus, the increased salience of gender and ethnic characteristics increases the likelihood that individuals will identify with such characteristics (as compared to others) and facilitates affective changes tied to in-group/out-group designations that themselves drive social categorization processes (van Knippenberg et al., 2004; Bell et al., 2011; Reagans, 2013). As the severity and extent of social categorization increases, so should the member coordination complexity within a work unit, essentially increasing the relevance of collective resources such as productive capacity to unit performance.

In sum, the analytical combination of the “most-controlled” performance outcome (gross sales per guest) with the interactions dependent on the most visible and salient demographic characteristics (ethnicity and gender) suggest a rationale by which the observed significant interactions would emerge while other proposed diversity-based interactions reliant on different characteristics (age and tenure) and examining different outcomes (customer satisfaction and gross sales) would not. Finally, simultaneous investigation of all proposed interactions as a single block within full-model specifications revealed no effects substantively different from those detected in individual hypothesis tests (*see Table 8*). However, the positive and significant interaction between productive capacity and ethnic diversity as a predictor of gross sales per customer remained marginally significant in the accordant full model specification (b = 15.25; β = .07; p = .10), providing slight evidence of the robustness of this interaction effect.

Practical Effects, Theoretical Quandaries, and Limits of the Sample

Given the results of this study, productive capacity appears to be of practical significance, at least to the organization investigated here. In tests of *Hypothesis 1*, capacity emerged as a significant predictor of both customer satisfaction and gross sales. Given the nature of the customer satisfaction measure provided by the partner organization, an increase from zero capacity to a “perfect” capacity value of +1.00 would amount to an increase of 13 percent in the proportion of respondents giving the organization “excellent” ratings (just over three standard deviations’ worth of change). The same movement from zero to perfect capacity equates with an increase of $278,905 in monthly gross sales for the average unit. While capacity generally did not emerge as a significant main effects predictor of gross sales per guest, its interaction with ethnic and gender diversity, respectively, suggest other effects of practical significance.

For instance, movement from zero to perfect capacity in a unit with high ethnic diversity (i.e., one standard deviation above the mean value) equates to an increase in gross sales per customer of $4.47. Since the average monthly customer count is 15,075, this suggests a revenue increase of roughly $67,385 per month. Similarly, zero-to-perfect movement on capacity in a gender diverse environment, equates to an increase of $4.13 in gross sales per customer and, ultimately, an increase of about $62,260 in monthly revenue per unit. The practical implications of the detected interaction effects also point to actionable advice for managers. Given the evidence that capacity may generate larger effects on performance in more diverse settings and assuming that organizations function with limited resources, efforts to build and maintain capacity can be meaningfully directed towards those units where the greatest return on the organization's investment can be achieved.

The practical impacts of capacity, both as a construct in its own right and as a measure of collective-level functional potential, are also contingent, to some extent, on its relationship to its conceptual kin, collective turnover. While the theory underlying the capacity construct stands on its own, unless the construct and the measure demonstrate enhanced predictive validity relative to turnover, its adoption and use by researchers and practitioners alike may be limited. In post hoc analyses examining predictive validities of capacity and turnover respectively, there were hardly any differences (capacity→gross sales: $\beta = .21$; $p < .01$; turnover→gross sales: $\beta = -.20$; $p < .01$; capacity→customer satisfaction: $\beta = .21$; $p < .01$; turnover→customer satisfaction: $\beta = -.23$; $p < .01$; capacity→gross sales per guest: $\beta = .06$; NS; turnover→gross sales per guest: $\beta = -.10$; $p < .05$).

Examination of correlations of capacity with turnover ($r = -.93$) suggest the two, at least for the sample considered here, share considerable conceptual space. The strength of this correlation may decrease in other samples, for instance, those in which employee time-to-proficiency is longer than six months or where the nature of the task environment is more interdependent. Capacity also shared significant correlations with raw employee tenure (*r* = .57) and the annual stability rate (*r* = .84), calculated as the number of organizational members who are present at the beginning of the observation period and remain for the entire observation period divided by the total number of beginning members (Price, 1977: 17). Turnover's correlations with the same measures (tenure: *r* = -.49; stability: *r* = -.83) essentially mirror those of capacity.

Whether this close relationship between capacity and turnover is a characteristic of the current sample or persists across a wide variety of organizations remains to be seen. In performing the foregoing analyses, however, relatively unique characteristics of the current sample became apparent. For instance, across the entire population of organizational units (from which the 400 analyzed units were randomly sampled), only a handful were permanently closed. Combined with a mean unit age of nearly 24 years, this suggests that the organization has its operations down to a science with respect to where new units are placed and to the production and provision of goods/services combinations. Given the high locational dependence of the performance measures examined here, it becomes difficult to determine what proportion of performance is reliant on human resources and what is reliant on putting a unit in the right location. Additionally, early site visits suggested that much of the skill necessary for successful unit-level operation may be built into the systems of the organization as opposed to the people who work for it. If this is the case, capacity may be important up to the point of a relatively low threshold—e.g., a unit may need just enough capacity to push the right buttons and flip the right switches—after which, additional capacity does little, if anything, to improve performance. Such a situation may essentially relegate capacity to a status as the simple complement to turnover in the current sample and might explain the pattern of correlations discussed above.

Directions for Future Research

As the foregoing discussion suggests, the first and most obvious step forward surrounds replication of the analyses performed here in different samples with different characteristics. Specifically, re-analysis of the hypothesis that capacity predicts performance in a sample with a greater level of task-environment complexity, that is less subject to locational influences on performance, where the time frame necessary to achieve individual proficiency is relatively long, and where the interactions of employees are more salient in determining performance outcomes may indicate a stronger capacity-performance relationship than that observed here and, additionally, may shed more light on the empirical proximity of capacity to turnover. Such re-analysis may be especially valuable in the context of medical or software development teams where the characteristics of fluid work demands necessitate frequent and complex interaction among team members and the time necessary to become proficient is likely much longer than the six months modeled here.

Beyond this, and where possible, multiple measures of member movement (e.g., the stability rate) should be calculated to establish convergent and divergent validities of capacity with related constructs. Despite the limitations of the current sample, capacity did emerge as a predictor of performance across many of the tested models. Having established such performance effects, another fruitful stream of future research may be found in the location and investigation of antecedents of capacity. While employee retention, and the human resource practices that encourage it, appears as a key input to capacity, other less obvious aspects of capacity and how it operates may warrant future investigation.

Thus, in addition to establishing antecedent-capacity-performance relationships, refinement of the capacity model itself is in order. In the current work, for instance, all employees were modeled as needing six months to achieve proficiency in their respective jobs. While this parameter was chosen as a result of interviews with key organizational members indicating its accuracy for the sample, in reality this number likely varies to some extent by job. Future work considering differences in time-to-proficiency across employee positions would increase the accuracy of the measure and the conceptual model that supports it and further, would be valuable in yielding information regarding the sensitivity of the capacity measure to time-to-proficiency assumptions.

In the same vein, capacity may be more important to, and more predictive of, unit-level performance, in core (versus peripheral) employee groups (Humphrey et al., 2009; Hausknecht & Holwerda, 2013). While, in the current work, all employees were treated as uniformly integral to unit-level operations, if core employees exert "extra" influence on performance outcomes as compared to peripheral employees, treating them as making uniform contributions to unit-level capacity may create a source of deficiency in the measure and attenuate observed relationships. Another refinement to the capacity model warranting future research surrounds the relative impacts of voluntary versus involuntary departures.

Specifically, voluntary departures may be more damaging to capacity, and ultimately performance, as they are generally neither anticipated nor planned for by the work unit. The damaging effects of involuntary departures, in contrast, may be planned for to some extent—e.g., having a replacement employee in the waiting—thus lessening the degradation of capacity at the unit-level. Work considering and modeling this possibility would once again improve the accuracy of the capacity measure and may help distance it from traditional notions of turnover rates, both conceptually and empirically.

Stepping away from capacity as a construct in its own right and toward its status as a member of a broader class of collective resources, other research investigating how such resources operate in the context of complex work environments is in order. Recalling the second central proposition of the current work, collective resources were argued to be more central to performance under conditions of greater complexity. Following the work of Espinosa and colleagues (2007), this study represents only the second direct test of this proposition known to the author. Given the oft repeated call to examine organizations while considering the effects of context and growing evidence that the relationships between collective resources and performance are, to some extent, dependent on contextual features such as work environment complexity, further investigations of these relationships are in order whether or not the collective resource in question is productive capacity.

Conclusion

In conclusion, this study sought to investigate the role of productive capacity in driving collective performance and, in so doing, provided initial empirical validation of Hausknecht and Holwerda's (2013) capacity-based perspective. Beyond the particulars of the various models, capacity emerged as generally predictive of performance, signaling, at least for now, its worthiness as a construct and the value of the measure, warranting its future use and investigation. Additionally, the conceptual space of capacity was developed, with the construct positioned as a collective resource subject to contextual effects. While the supporting evidence was meager, it is also promising as, under the right analytical conditions, an interaction between capacity and context emerged to predict performance. While characteristics of the sample may have obscured proposed relationships, the same characteristics suggest that the tests performed as part of this work were conservative in nature. Thus, with different samples and continuing model refinements, capacity, as a measure and conceptual perspective, may empirically make good on its theoretical promise.

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